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TIME-LAPSE IMAGE PROCESSING FOR ESTIMATING CONSTRUCTION EQUIPMENT EMISSIONS

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ABSTRACT

Non-road mobile machinery (NRMM) contributes significantly to environmental pollution. As part of lean construction methodologies, construction equipment emissions can be monitored remotely by analyzing its working states over time. This offers a viable alternative to expensive, simplified, or portable emission monitoring systems. However, the complex and dynamic aspects of construction sites make it difficult for humans to follow equipment activity. This leads to manual and time-consuming site resource management. This paper proposes automating the task of equipment emission monitoring as part of the more significant goals in lean construction by applying Artificial Intelligence (AI) to photography from a time-lapse camera that oversees a construction site. A Deep Learning model is trained to detect several pieces of equipment on the construction site. The proposed method further tracks the resources to predict whether it is operating between consecutive timestamps. Observing the activity state of the equipment, the respective emission values of the equipment are calculated according to historical and calibrated benchmarks. The results demonstrate a promising method applying existing surveillance technology that, while it also automates parts of construction site operations monitoring of lean schedules, simplifies the process of tracking emissions with respect to construction equipment operations on construction sites. Further work is suggested to acquire higher temporal resolution data and improve data labeling, thereby performing semantic segmentation of equipment for better tracking results for lean construction purposes.

KEYWORDS

Computer vision, Deep Learning, Object detection and tracking, Time-lapse camera, Lean construction equipment operation, Greenhouse gas emissions.

INTRODUCTION

Waste, pollution, and greenhouse gas (GHG) emissions are omnipresent in construction operations. Construction machinery, for example, is still predominantly diesel-powered and, consequently, a major contributor to GHG emissions and global warming (Jassim et al., 2018). In Denmark, Non-Road Mobile Machinery (NRMM) accounts for nearly half of CO2 emissions in the construction industry and emits harmful pollutants, including NOx and CO2 (Winther & Nielsen, 2023). The European Union (EU) has, therefore, enforced threshold limits to regulate NRMM emissions. Stage V standards set stringent limits on pollutants such as NOx and

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hydrocarbons from NRMM, requiring advanced technologies like selective catalytic reduction (SCR) and diesel particulate filters (DPFs) for compliance (European Union, 2016).

NRMM emission levels are monitored with various expensive emission sensor technologies (Abolhasani et al., 2008; Andrade & Teizer, 2023; Teizer & Wandahl, 2022). However, the limited installation of emission sensors on construction equipment necessitates developing and implementing indirect emission monitoring methods (Barati et al., 2021). Computer vision has been widely implemented to automate construction site monitoring (Seo et al., 2015; Fang et al., 2018). The prospect of automation can help efficiently monitor construction resource activities for emission estimates. Object detection algorithms can be used to understand the number and work time of different equipment on the construction site (Fang et al., 2018; Xiao et al., 2020). Such information, while generally applicable to many tasks in lean construction management, can then facilitate estimating the emissions by the equipment.

This study presents a method of utilizing time-lapse photos with 15-minute time intervals for tracking equipment operations and estimating emissions. This method aims to leverage a vision-based approach to minimize reliance on emission sensors installation. Using time-lapse photos rather than continuous video data significantly reduces vision data that needs to be processed. As such, this study contributes to the mission of lean construction and Digital Twin for Construction Safety and Health, reducing waste, emissions, and, among others, unnecessary fossil fuel consumption (Teizer et al. 2020; Johansen et al. 2024; Teizer et al.; 2024).

RELATED WORK

OBJECT MONITORING AND DETECTION

Time-lapse cameras offer cost-efficient solutions for construction site status monitoring. Early work with such cameras by Bohn and Teizer (2010) has shown these to work cost-effectively and benefit construction management while maintaining the privacy of the workforce. More recently, Kim et al. (2019) have demonstrated that object detection as part of deep learning techniques involves automated identifying and locating multiple objects within an image. This progress shows that technology not only records but also assigns class labels and bounding boxes to individual objects to precisely differentiate their locations and timestamps. There have been several object detection models over the past decades that outperform each other in the different benchmark datasets. Once available, data from such approaches serves as evidence and offers promising applications in lean construction management.

Much progress has also been made on the computational algorithms that process raw data feeds from a time-lapse camera. This can assist a lean construction manager who would like to rely on such data streams to enhance decision-making. For example, EfficientDet, which was released by a Google research team, is known for its efficiency and high accuracy in creating information that humans would not be able to create manually (Tan et al., 2019). It uses compound model scaling to balance accuracy and speed. It is particularly noted for its scalability in realistic applications, like construction needs, making it suitable for a range of applications from mobile devices to high-performance systems.

Another example is Detection Transformer (DETR), a product of a Facebook AI team. It introduced a new paradigm by treating object detection as a direct set prediction problem, which has shown impressive results on benchmarks like COCO (Carion et al., 2020). Such approaches simplify the detection pipeline by eliminating the need for hand-crafted components like anchor boxes. For lean construction applications, it means simplifying the process by providing assistive tools that would otherwise not exist but are needed to enhance decision-making.

The world of lean construction and construction information and communication technology (ICT) has yet to achieve the outlined benefits (gathering raw project site status data, converting it to valuable information, and applying project status knowledge). One additional example of how far the world of technology has progressed in recent years is the YOLO (You Only Look Once) series (Bochkovskiy et al., 2020; Gillani et al., 2022; Redmon & Farhadi, 2016 and 2018). It continues to evolve with each version, improving the accuracy or speed of detecting target objects in images. For example, YOLOv8 has been used in this work as it incorporates anchor-free detections and a decoupled head approach (Jocher et al., 2023). The framework of YOLOv8 makes it even more suitable for lean construction applications due to the various factors such as flexibility, speed, accuracy, and ease of use.

EMISSIONS MONITORING

Emission sensors have been implemented at the exhaust machinery systems to measure the emissions of NOx and CO2 during operation. Portable Emissions Measurement Systems (PEMS) are designed to measure and analyze emissions from road vehicles and NRMM (Abolhasani et al., 2008; Cao et al., 2016). Simplified Emission Measurement System (SEMS) offers a cost-effective alternative for its compact size and straightforward installation process (Teizer & Wandahl, 2022). However, emission sensors are not universally implemented in all equipment. Alternative methods have been developed to estimate energy consumption and emissions based on engine performance and operational behaviors of each type of equipment. Data obtained from different sensors can be utilized for emission estimates. For example, telematics systems provide comprehensive monitoring of mechanical conditions, including parameters such as speed, idling time, and fuel consumption (Monnot & Williams, 2011).

Similarly, Real-Time Locating Systems (RTLS) are capable of recording and mapping the movement of vehicles, offering valuable insights into their operational patterns (Thibault et al., 2016). All these data points are relevant to lean construction site operations. These can be utilized to analyze the operational status of equipment, serving as a foundation for various models, including discrete models and machine learning approaches, to estimate emissions. Machine learning models, such as Random Forest, have demonstrated good performance in predicting emissions using data from accelerometer and gyroscope sensors (Shahnavaz & Akhavian, 2022). Likewise, a discrete model has been developed to analyze duty cycles and emissions related to engine performance for specific types of equipment (Hong et al., 2024).

METHODOLOGY

This section presents the method adopted in this work, as shown in Figure 1. A high-resolution camera mounted on Tower crane monitored the high-rise construction site in Aarhus, Denmark, to understand the live site operations of multiple heavy construction equipment involved in schedule-driven foundation piling. Fifteen equipment types were observed operating on the construction site for different activities.

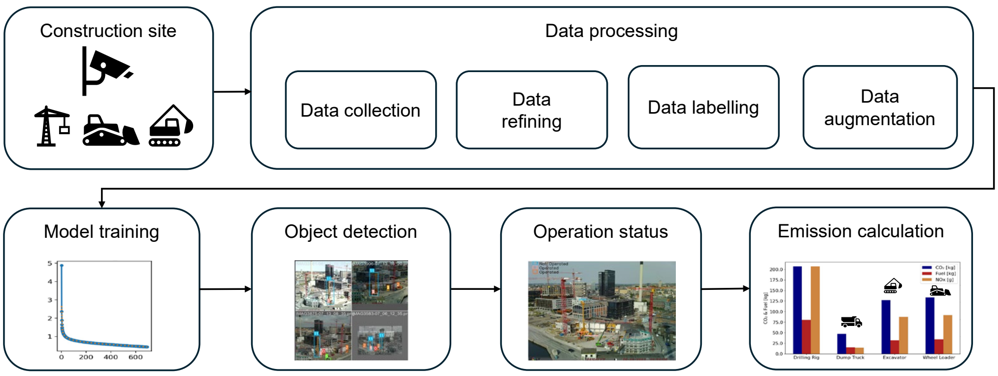

Figure 1. Using time-lapse photos for activity-based emission estimate

Time-lapse photos were collected with a temporal interval of 15 minutes by default, and the equipment in the photos was then labeled manually to train a Deep Learning model, YOLOv8. YOLO v8 was chosen for object detection as it has one of the best performances with anchor free detections and improved accuracy. The pipeline for Yolov8 handled by Ultralytics (Jocher et al., 2023) is an open-source code with great ease-of-use. The trained model detects the individual machines in the photos. The model provides a bounding box detection and classification of the equipment as output. A 'status of operation' algorithm then predicts whether the equipment operated between two consecutive timestamps. The temporal distribution of each equipment's activity is subsequently analyzed, and NOx emissions, CO2 emissions, and fuel consumption are estimated on the basis of average emission rates measured from historical measurements from experiments.

DATA COLLECTION AND PREPROCESSING

Data collection

To train the Deep Learning model, RGB data was collected using a crane camera and collected for 18 months. The time-series data collected were images with an interval of 15 minutes during the working hours of the construction site, approximately from 07:00 to 17:00 every workday. The total number of images collected was 11,562, out of which 9,303 images have been labeled due to the impact of several artifacts that affect the data quality. 90% of the total usable images were used for training and 10% as validation data. Some of these artifacts can be seen in Figure 2, which makes it not useable in this study. The images had a resolution of 1600x1200 pixels, as shown in Figure 3.

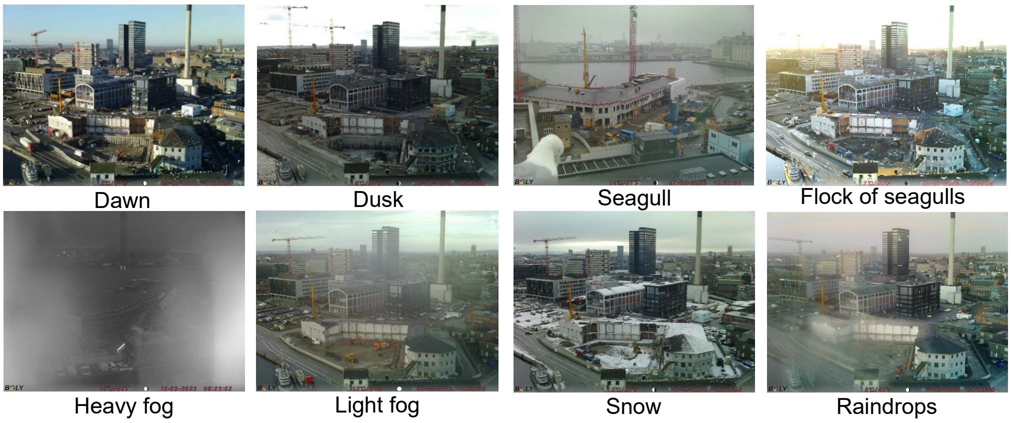

Figure 2. Artifacts that affected the data collection and repository

Figure 3. Sample time-series data collected on 19-06-2023 between 07:20 and 08:05

Data labeling

The training data was labeled using "LabelMe", an open-source data labeling tool (Wada et al., 2021). For the specifics of a detection model, the labeled data needs to be in the form of bounding boxes (i.e., the top left point and the bottom left point of the rectangular label). Object detection model is trained with bounding box labels and not object segments as the objects have complex structures which is challenging to perform object segmentation. The collected data consists of 15 heavy construction equipment, including excavators, wheel loaders, dump trucks, concrete machines, containers, drilling rigs, and anchorage machines. Hence, the training data contains different labels, as illustrated in Figure 4. The data label for each image is saved in JSON format. Various data augmentations have been performed to further enhance the robustness and performance of the Deep Learning model.

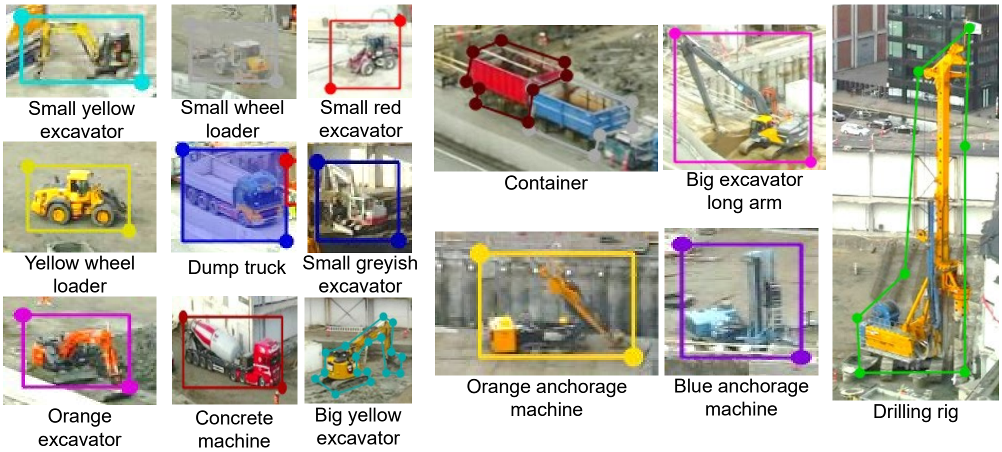

Figure 4. Labeled pieces of heavy construction equipment for construction site monitoring

Data augmentation

Continuous and random selection of various techniques of augmented data is used during the training of the Deep Learning detection model. The process of data augmentation helps the model to detect objects in different conditions. The data augmentation techniques used in this study are summarized in Table 1.

Table 1. Augmentation techniques used on the original training dataset

Type of augmentation	Value
Rotation	[0-30] (+/- deg)
Translation	0.1 (fraction)
Scaling	0.5(+/- gain)
Shear	0.5 (+/- deg)
Flip left/right	0.5 (probability)
Mosaic	[0.1-0.9] (probability)
Mix-up	[0.1-0.9] (probability)

DEEP LEARNING MODEL TRAINING

The main goal of the proposed model is to detect and classify the respective equipment. YOLOv8 was used as the base model for the training. Its network can be built with different architecture configurations by modifying the amount and type of layers, and the different hyperparameters that affect the weights of the network. To properly choose the best architecture, several tests were performed to assess the performance of the network. The weights of the underlying deep feature extractor (i.e., YOLOv8 network backbone) were optimized to minimize the loss of the bounding box detection and classification. A summary of the tested models and corresponding results can be seen in Table 2 and Figure 5.

The results include Precision, Recall, and Mean Average Precision (mAP) for detecting the equipment. The results from training the YOLOv8 Model#1, the ‘n’ variant, which has over 3.2 million parameters, and Model #2, which is an ’l’ variant with around 43.7 million parameters, can be seen in Figure 5. Model #2 clearly has better training results, and hence, it has been chosen to detect the equipment.

Table 2. Training model description and parameters

Model	Details
#1	Yolov8n – 3.2M parameters
#2	Yolov8l – 43.7M parameters

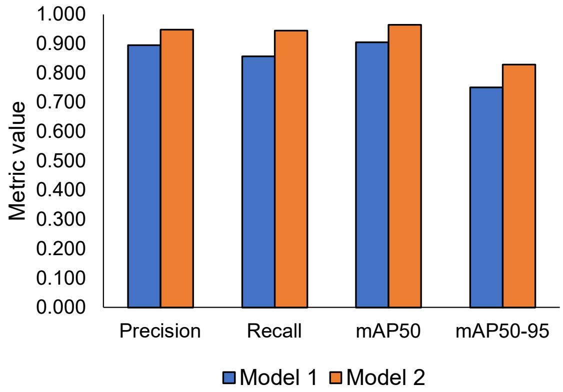

Figure 5. Results for different metrics of each model

ACTIVITY-BASED EMISSION ESTIMATE

The detected bounding boxes of the equipment in the images with its class type are then passed through the ‘status of operation’ algorithm, as seen in the pseudo-code in Table 3. The algorithm in this work predicts whether the equipment in the consecutive images has been operating based on its location and orientation change from the previous to the next frame. The algorithm uses x, y (center of the bounding box) and w, h (width and height of the bounding box) of each piece of equipment in the consecutive timestamps to predict whether the equipment has been operated.

Table 3. Pseudo code of ‘status of operation’ algorithm

Algorithm 1: ‘Status of operation’

```
Input: Bounding Box (BB) center (x, y), width (w), height (h), timestamp (t)
Output: Status of operation
if BB (x, y) at t-1 – BB (x, y) at t <= threshold then
   if BB (w, h) at t-1 – BB (w, h) at t <= threshold then
      status = “Not operated”
   else
      status = “Operated”
   end if
else
   status = “Operated”
end if
```

While a (lean) construction manager might be tasked to overlook a construction site in higher detail due to the limitations of achieving a higher temporal resolution (more frequent time-lapse imagery was not permitted), the duty cycle of the machines (e.g., drilling rig, excavator) was simplified into two main statuses: (a) operating and (b) not operating. The equipment status is classified as ‘operating’ during the intervals captured by time-lapse photos if its state changes (e.g., position or status). Following practical examples in lean construction productivity or work sampling assessments, these can be the drill rig (a) moved its location by 10m, (b) rotated its upper body from its base structure by 10°, or (c) lifted or lowered its rotary drive or drilling tool by a few meters. Similarly, other equipment has typical behavior to classify (non-) activity.

The output categories of the 'status of operation' algorithm that identifies the activity class for each type of equipment are listed in Table 4. For the drilling rig, detected movement is interpreted as 'drilling', while the absence of movement indicates 'idling'. For dump trucks, detected movement is interpreted as 'driving'; otherwise, the truck is 'loading or idling'. Similarly, detected movement is assumed to be 'operating', otherwise, 'idling' for the excavator and wheel loader. Note that the preliminary research efforts have focused on simplified output categories, and the results refer only to one observation day. Data from being off-site or outside the camera's field-of-view were not considered.

Table 4. Identified activities and emissions of construction machines for one observation day

Equipment	Activity	NO_x (10^{-3} g/s)	CO_2 (g/s)	Fuel (g/s)
Drilling rig	Drilling	18.48	20.51	6.49
	Idling	13.80	5.38	1.71
Excavator/ Wheel loader	Operating	3.77	18.08	5.34
	Idling	2.80	2.20	0.50
Dump truck	Driving	1.03	2.10	0.65
	Loading or Idling	0.87	1.21	0.38

Table 5. Evaluation metrics for Model #2

Precision	Recall	mAP50	mAP50-95
0.948	0.945	0.964	0.829

Emissions were calculated using a discretization model, which determines the emission rates produced by each equipment during specific activities. The emission rates associated with each activity were derived and adjusted based on previous studies, presented in Hong et al. (2024). In this study, the wheel loaders' emission rate was approximated using excavators' data. The model calculates average NOx, CO2, and fuel consumption emissions for each machine's duty cycle activity. This calculation is achieved by combining a probability matrix with emission heatmaps corresponding to engine load and speed.

RESULTS

DETECTION RESULTS

The results show that Model#2 achieved the highest accuracy on the validation target data. The values for the evaluation metrics for Model #2 are summarized in Table 5, and representative results to classify the target images are shown in Figure 6. Model#2 performed with great accuracy in predicting the bounding boxes and the class of the equipment. The operation function's status predicts the equipment's operation with good accuracy even though the data set has limitations. First, while some equipment has operated (i.e., drill rig, wheel loader, and excavator), the 15-minute gap between the consecutive images infers that a dump truck must have arrived (yellow arrow in Figure 7). Overall, the confusion matrix of the Model#2 prediction on the validation data shows very few misclassifications of the equipment (0.3%). The labels are shown in Figure 8.

EMISSION ESTIMATE RESULTS

The 'status of operation' algorithm was applied to the object detection results from the time-lapse photos. The status of 4 pieces of equipment over a day is illustrated in Figure 9. The dump truck was absent from the site for most of the day, as it was hauling the excavated earth to an off-site dumping location. The other equipment operated for most of the day. However, the excavator and wheel loader occasionally did not appear in the images, which was attributed probably to occlusions by buildings or other objects. The status of the equipment when it was outside of the camera's field-of-view was still considered operating if the interval was less than two consecutive images (15 minutes).

Figure 6. Detection of equipment and its operation status on 26-06-2023

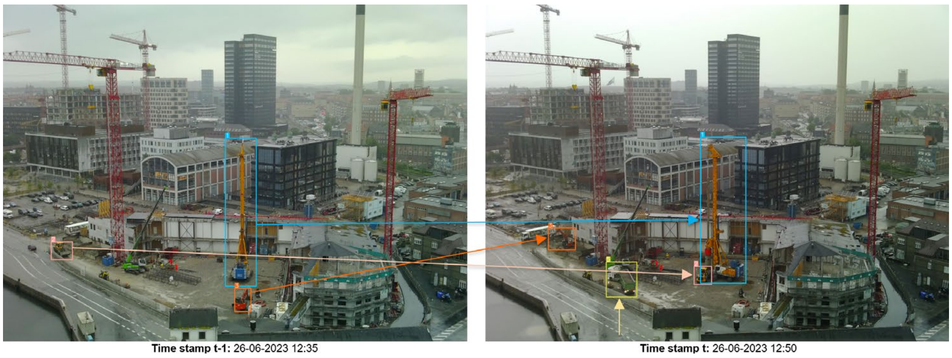

Figure 7. Detection and tracking of machines between two consecutive images

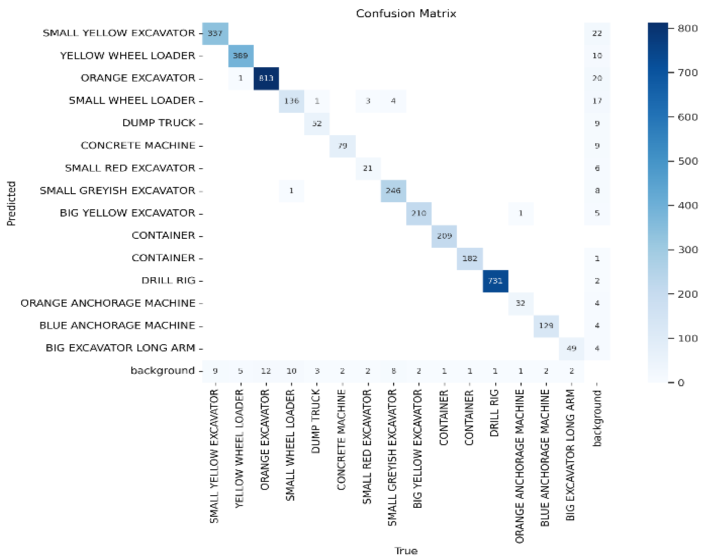

Figure 8. Confusion matrix for Model#2 predictions

Such automatically generated equipment status information can provide valuable insights into project status knowledge and, thus, the further planning of construction schedules and required resources. The lean managers responsible for the project are anticipated to use the generated knowledge well. However, applying the proposed method within the core scope of this work described the earlier outlined NOx- and CO2-emissions and fuel-consumption values of the four pieces of construction equipment. Their estimates for (only) one workday of the observed data are shown in Figure 10.

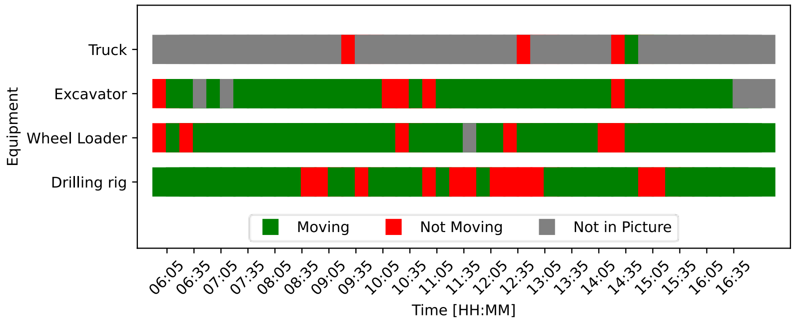

Figure 9. Recognized activities of equipment during the selected observation day

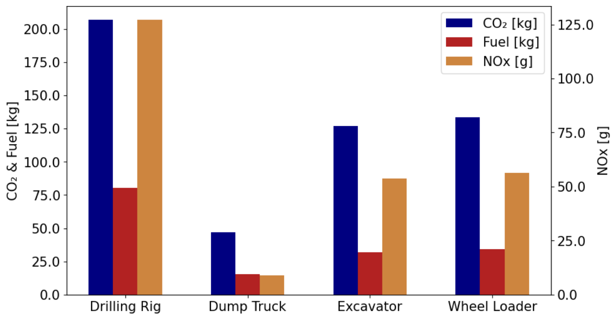

Figure 10. Emission estimates throughout the selected observation day

DISCUSSION

The results demonstrate that the proposed method offers a reasonable approach to predicting emissions from selected pieces of construction equipment. Potential for camera monitoring exists to reduce the dependency on expensive installations of emission sensors on every construction equipment. This work accurately detected selected equipment on the construction site with a YOLOv8 model. The detection and classification of the bounding box and label of the equipment have been very accurate. The equipment detection and emission estimate algorithms were then implemented on timelapse photos collected from the site, demonstrating the viability of using timelapse photos for emission estimates.

Nevertheless, there were certain limitations to this work. The absence of ground truth emission measurements prevented direct evaluation of the results, and the method was only tested on limited data for feasibility validation. Future work could address this limitation by incorporating emission sensors to collect real-world data and comparing it with the predicted outcomes. Such efforts would help further optimize and validate the proposed method. Additionally, the prediction of the equipment's operation status was made using a custom-built function that uses a bounding box and labels of the equipment. This is not the optimal way to predict whether the equipment has operated between consecutive timeframes. A further limitation arises from the low temporal resolution of the available data for this construction site, which has provided images approximately every 15 minutes. This restricted the work to apply state-of-the-art deep learning tracking algorithms like Deep SORT (Wojke et al., 2017) or Byte

Track (Zhang et al., 2021). These have the potential to get even better tracking results on the equipment. Instead, this work used an object detection model and a custom-built algorithm to predict the movement or status of real construction site operations.

However, these limitations pose opportunities for future work to record data with higher temporal resolution. Suggested are data update rates to achieve a more precise and accurate emission prediction. Further improvements could be made with semantic segmentation of the equipment instead of the bounding box. For example, the results could be substantially improved by predicting the movement and orientation with Intersection Over Union (IOU) of equipment masks. However, the semantic labeling of equipment is time-consuming, requiring more research resource allocation towards the labeling efforts. Like other existing research efforts have shown, future work can also utilize vision for activity monitoring of construction equipment in other applications, such as noise emission control (Babazadeh et al., 2024) and other worthwhile construction site monitoring applications (Bohn & Teizer, 2010). Additional potential exists for optimizing site layouts and resource allocation by minimizing emissions based on limited on-site measurements for comparison. Basic Discrete Event Simulation (DES) of earthwork models can be (re)discovered in future work. Furthermore, this activity recognition monitoring method can be adapted, enabling multi-objective optimization of the construction process and life cycle analysis regarding cost and environmental impact.

CONCLUSIONS

This study introduced a vision-based method for estimating emissions from construction equipment operations. The method (a) identified equipment in various operational states by analyzing object detection results from consecutive images and (b) calculated emissions based on the temporal distribution of operation statuses. Preliminary validation was conducted on a subset of the data set, which includes 18 months of time-lapse photos taken by a fixed camera at 15-minute intervals on the deep excavation construction site.

A YOLOv8 deep learning model, trained on labeled images of 15 equipment types, achieved precision and recall scores of 0.948 and 0.945, respectively. For practical reasons, the model was applied to a single working day to detect the operation states and to estimate the respective emission values. The results demonstrate the overall feasibility of this approach for quick and cost-effective emission estimation. Compared to deploying emission sensors on older and non-compatible equipment, the proposed vision-based method significantly reduces investment and related operational efforts. As this study focused on the preliminary efforts, foremost the gathering of the data set and a method for its analysis, only emission estimates at lower temporal resolution were possible. This limitation requires further comparisons with ground-truth measurements. Future work should examine the impact of temporal resolution on the accuracy of emission estimates.

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