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LIGHTHOUSE PROJECT #28: THE APPLICATION OF COMPUTER VISION TO MEASURE PRODUCTIVITY ON CONSTRUCTION SITES

FINAL REPORT

LEVEL CROSSING REMOVAL PROJECT

sightdata

THE UNIVERSITY OF MELBOURNE

Australian Government Department of Industry, Science and Resources

Cooperative Research Centres Program

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CONFIDENTIAL:	NO
Author/s of this report:	Dr Philip Christopher, Dr Aravinda Sridhara Rao, Nathan Nguyen, Prof Tuan Ngo
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Disclaimer

ABBREVIATIONS

3D	three dimensional
AI	artificial intelligence
AWP	Alliance Work Package
BCM	bank cubic metres
BIM	building information modelling
BoS	basis of schedule
CCTV	closed circuit television
CNN	convolutional neural network
CV	computer vision
CVAT	computer vision annotation tool
DARUPTO	Design, Access, Approval, Available, Relocation, Unsuitable, Procurement, Traffic, Out-of-sequence
EHS	environment, health and safety
FNR	false negative result
FOV	field of view
FPR	false positive result
GMM	Gaussian mixture model
GPS	global positioning system
HoG	histogram of gradients
IMU	inertial measurement unit
IoT	Internet of Things
LSTM	long-short-term-memory
LXRP	Level Crossing Removal Project
LCM	loose cubic metres
LCY	loose cubic yards
MAE	mean absolute error
ML	machine learning
NATM	novel Austrian tunnelling technique
OTR	other than rock
PLM	plant, labour and materials
PPE	personal protective equipment
PTZ	pan, tilt, zoom
ResNet	residual neural network
RFID	radio frequency identification

RMSE	root mean square error
ROI	return on investment
SIFT	scale-invariant feature transform
SME	small and medium enterprise
SSD	single shot detector
SVM	support vector machine
TLD	tracking-learning-detecting
UWB	ultra-wideband
V&V	verification and validation
YOLO	you only look once

EXECUTIVE SUMMARY

This project aimed to integrate computer vision and artificial intelligence (AI) technologies for productivity monitoring on level crossing removal sites. This report presents the findings and recommendations from a comprehensive trial conducted at the Dublin Road Level Crossing Removal site in Ringwood East, Victoria. The primary objective of this initiative was to explore the potential of automated data collection and analysis using visual data (images and videos) to enhance the accuracy, efficiency, and real-time monitoring of productivity metrics. Key focus areas included tracking earth removal volumes, equipment utilisation, labour deployment, and overall site activity. Through a collaborative effort involving the Level Crossing Removal Project (LXRP), The University of Melbourne, and technology provider Sightdata, a robust computer vision system was developed and deployed at the Dublin Road site. This system leveraged computer vision and AI algorithms to detect and track objects, count bucket loads, monitor truck movements, and identify personnel numbers on-site while ensuring privacy requirements were met.

The trial yielded promising results, demonstrating the capability of computer vision to provide reliable productivity insights. Notably, the AI model exhibited strong performance in counting bucket loads of dirt, with count accuracy rates ranging from 89% to 99% across multiple days. However, challenges were observed in people counting, with a tendency to undercount larger groups; and object detection, where vehicles were prone to overcounting during peak activity hours. Compared to traditional manual data collection methods, which are susceptible to human error, inefficiencies, and delays in reporting, the computer vision approach offered several advantages. These include real-time monitoring, reduced labour costs, and the potential to gain timely insights not previously available. While the trial highlighted the significant potential of computer vision in construction productivity monitoring, it also identified areas for improvement. Environmental factors, such as sun glare, lighting conditions, and occlusions, were found to impact model performance. Additionally, the complex interactions between various equipment types and the diverse range of machinery used on construction sites posed challenges for automated tracking efforts, especially when attempting to distinguish between similar equipment. The project also faced additional challenges related to onsite acceptance from workers who were concerned about privacy related issues for the workforce.

To address these challenges and facilitate broader adoption of computer vision technologies, the report provides recommendations focused on optimal camera placement, additional site-specific training, stakeholder engagement, and the establishment of governance structures. Emphasis is placed on collaborating with site teams and workers to ensure transparency, address privacy concerns, and foster a culture of innovation while prioritising worker safety and rights. Looking ahead, the report explores future applications of computer vision and AI in areas such as automated tracking of personnel, equipment uptime monitoring, personal protective equipment (PPE) detection, and real-time footage integration. Additionally, the potential for extending these technologies to earthworks monitoring, environmental compliance, and civil infrastructure productivity tracking is highlighted, highlighting the versatility and scalability of computer vision solutions in construction. In conclusion, the Dublin Road Level Crossing Removal trial has demonstrated the transformative potential of computer vision and AI in revolutionising construction productivity monitoring. By addressing the identified challenges and fostering a collaborative approach with stakeholders, the LXRP and the construction industry more broadly are well placed to adopt these cutting-edge technologies, driving efficiency and innovation across the construction industry.

1. PROJECT OVERVIEW

1.1 Introduction

This report presents the findings and recommendations from a pioneering initiative undertaken by the LXRP to integrate computer vision and artificial intelligence (AI) technologies for productivity monitoring on construction sites. The primary objective of this initiative was to explore the potential of automated data collection and analysis using visual data (images extracted from videos) to enhance the accuracy, efficiency, and real-time monitoring of productivity metrics. The report covers the following key aspects:

1. Project Overview and Objectives: Background on the LXRP and the motivation for adopting computer vision technologies. Specific objectives and goals for productivity monitoring, including tracking earth removal volumes, equipment utilisation, labour deployment, and site activity.

2. Literature Review: Overview of existing research and studies on using computer vision for productivity monitoring in construction. This explores the different approaches, including sensor-based methods and computer vision-based techniques. Case studies are also presented demonstrating the application of photogrammetry, video analysis, simulations, and license plate recognition for earthmoving productivity monitoring.

3. Methodology and Approach: Details on the collaborative effort involving LXRP, The University of Melbourne, and technology provider Sightdata. Development and deployment of the computer vision system at the Dublin Road Level Crossing Removal site in Ringwood East, Victoria. Explanation of the AI algorithms employed for object detection, earthwork volume assessment, truck movement monitoring, and personnel analysis.

4. Trial Results and Findings: Evaluation of the computer vision system's performance in various productivity metrics, such as bucket load counting, people counting, and object detection. This section includes a comparison with traditional manual data collection methods, highlighting advantages and limitations. Finally, challenges are identified as well as areas for improvement, including environmental factors and complex equipment interactions.

5. Recommendations and Future Applications: Recommendations for optimal camera placement, stakeholder engagement, and the establishment of governance structures. Exploration of future applications, including automated tracking of personnel, equipment uptime monitoring, safety detection, and real-time footage integration. Potential for extending computer vision technologies to earthworks monitoring, environmental compliance, and civil infrastructure productivity tracking.

6. Implementation Considerations: Discussion on the role of stakeholders, such as workers, in fostering innovation while ensuring worker rights and safe working conditions. - Implementation guides focused on stakeholder engagement, justification, pilot projects, training, and communication.

7. Conclusion: Summary of the potential of computer vision and AI in improving construction productivity monitoring. Outlines challenges and the need for fostering a collaborative approach with stakeholders to drive efficiency, safety, and innovation across the construction industry. Finally, the success of the Dublin Road Level Crossing Removal trial is assessed, highlighting the potential benefits, challenges, and future opportunities for broader adoption and integration of computer vision technologies in the construction sector.

1.2 Background and Problem Statement

The current method of recording productivity on construction sites relies heavily on manual inputs provided by the various project alliances. However, this approach has inherent limitations that limit the accuracy and efficiency of data collection and, therefore, the results. One of the major issues is the frequent incompleteness and bias in the data, which severely restricts the insights gained from on-site performance indicators. Because the data relies on manual reporting, it is susceptible to human error, leading to inaccurate and inconsistent productivity measurements that can misrepresent the actual progress of the project.

Furthermore, gathering data manually is a time-intensive process that diverts valuable labour resources away from core construction tasks. This diversion not only affects productivity but also introduces the risk of delays and inefficiencies in the project timeline. Additionally, the painstaking effort required for accurate data collection and record-keeping can be burdensome and may not always provide an accurate reflection of the project's true productivity.

To address these challenges and enhance productivity monitoring, it is imperative to explore more automated and technologically advanced solutions that can provide real-time, accurate, and unbiased data on on-site performance. Such innovations can not only streamline the data collection process but also free up labour resources to focus on essential construction activities, ultimately leading to more efficient and reliable project outcomes.

1.3 Objectives

Integrating visual data and technology has become a transformative force in construction, offering a means to gain profound insights, make well-informed decisions, and significantly enhance project outcomes. This approach involves the autonomous capture, analysis, and interpretation of visual information, encompassing images, videos, and three dimensional (3D) models, to comprehensively understand and monitor various facets of the construction process in real time.

At the core of this innovation lies the utilisation of AI and machine learning (ML) algorithms, which play a pivotal role in further processing and comprehending visual data. These algorithms can extract invaluable insights and productivity measures from the visual information, enabling real-time decision-making in construction projects. For instance, AI algorithms can be employed to track and analyse the movements of construction equipment on-site by harnessing visual data. AI can monitor their usage, movement patterns, and utilisation rates by proficiently recognising and identifying different equipment types.

This wealth of information drives the deployment of equipment, facilitates proactive maintenance planning, and ultimately enhances the overall operational efficiency of construction projects. By harnessing the power of visual data and AI, construction stakeholders can embark on a transformative journey toward achieving greater precision, efficiency, and productivity in their endeavours.

2. LITERATURE REVIEW: COMPUTER VISION FOR PRODUCTIVITY MONITORING

Automated productivity monitoring brings many advantages to construction activities. It swiftly identifies potential project issues, enhances the likelihood of timely task completion, and reduces costs (Chen et al., 2022).

Earthwork activity is not just a component but the backbone of any construction project. It encompasses the excavation, transportation, filling, and compaction of soil. These tasks necessitate heavy machinery, such as excavators, trucks, and bulldozers, and are costly, potentially inflating the construction project's expenses. Hence, there is an urgent requirement to boost the productivity of construction equipment to enhance overall productivity and meet cost control objectives (Rezazadeh Azar & McCabe, 2012b).

Numerous research studies have developed automated approaches to monitoring the productivity of construction equipment. Various technologies have been employed to estimate the duration of equipment operation, quantify the amount of soil, and analyse the factors that influence productivity. By optimising the utilisation of construction equipment and resources, it sets the stage for improved efficiency and cost control. In contrast, manual equipment productivity monitoring is laborious and ineffective (Chen et al., 2022).

Tracking and analysing equipment efficiency is the first step towards enhancing productivity. Traditional methods rely on manual observation and recording of operational progress, which is time-consuming, expensive, and prone to errors. But with advancements in sensing, advanced cameras, information technology, wireless communication, and Artificial Intelligence, we now have the tools to automate monitoring construction equipment's productivity, making it more efficient and accurate (Chen et al., 2022).

2.1 Artificial Intelligence to Monitor Productivity

AI is a data-driven approach that has revolutionised the field of engineering. In the construction industry, it is a game-changer used for various tasks, including monitoring construction site progress, planning, and designing through generative AI, robust fleet management, risk mitigation, workers' safety, and pre-fabrication of structures. Its versatility and potential for automation make it an exciting and invaluable tool in the construction industry, promising a future of enhanced productivity and cost control (Abioye et al., 2021).

AI relies on data generated from sensors and manual logs to construct intelligent models that can learn patterns from the data and can be used to predict tasks. This includes five stages (Chen et al., 2022; Géron, 2022) listed below and shown in Figure 1:

- Data acquisition: data from sensors and logs are acquired from the construction sites, suppliers, contractors, and other personnel involved. Sensors can be of any type, including cameras, accelerometers, GPS, etc. Manual logs often involve the logbook containing the activities, timings, and other information.
- Data Cleaning: Often, we encounter missing data points, corrupted samples or incorrect values being aggregated. The data is cleaned using specific algorithms and expert knowledge to produce a clean and consistent dataset.

- Feature Extraction: To build a model, specific characteristics of the data samples are studied and identified to represent them. These patterns help AI models recognise similar patterns when fed new samples.
- Classification/Regression: This step builds AI models specific to applications. For example, to classify whether a dump truck is present in the video frame, we can train an AI model to classify each frame and output a response either "Yes" or "No". On the other hand, if we want to predict the productivity of the dump truck for a given day based on the previous day and consider whether the regression model will produce an output (a number) of, say, "4 hours" or "10 hours". For example, Activity Duration, Cycle Time, and Productivity all require regression models. Both classification and regression models are often used in parallel to generate outputs. For example, if we want to monitor the productivity of a construction site using video cameras, we need to identify dump trucks using classification models in each video frame and then estimate the productivity of dump trucks by analysing their movements from the videos using regression models.
- Prediction: The output response from the AI model is the predicted results. This could include Activity Duration, Cycle Time, Productivity, etc.

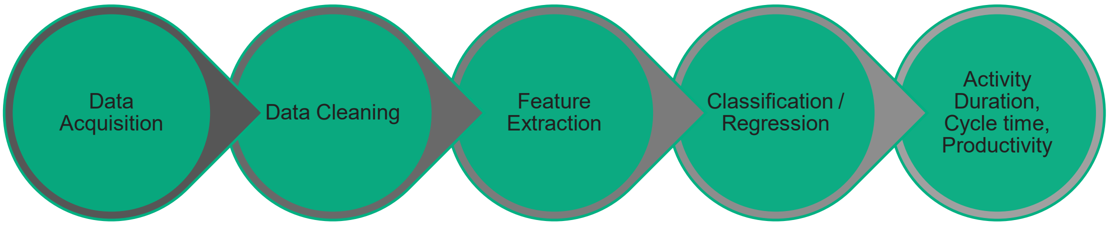


Figure 1. Typical data processing stages followed by AI algorithms

2.2 Monitoring Equipment Productivity

Equipment productivity monitoring can be divided into two main categories: sensor-based methods and computer vision (CV)-based approaches (Chen et al., 2022). Figure 2 shows the two major methods employed in the construction industry to monitor productivity.

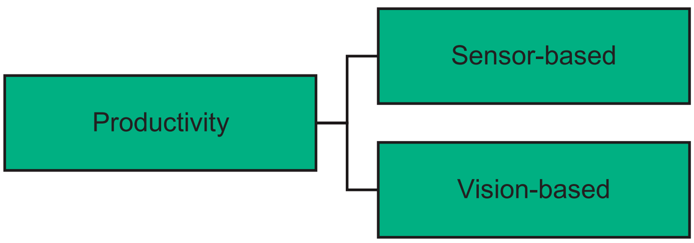


Figure 2. Two types of monitoring equipment productivity in the construction sector

Sensor-Based Methods

Sensor-based methods install sensors and tags [e.g., radio frequency identification (RFID), global positioning system (GPS), ultra-wideband (UWB), inertial measurement unit (IMU), etc.] on the equipment and the construction site to collect the position and pose information of the equipment. Accordingly, the work states and activities of the equipment are identified by analysing the data collected from cameras or sensors. For example, the location and trajectory data collected from the sensors can be used to estimate the activity of the equipment directly. Figure 3 shows the hierarchy and classification of sensor-based methods.

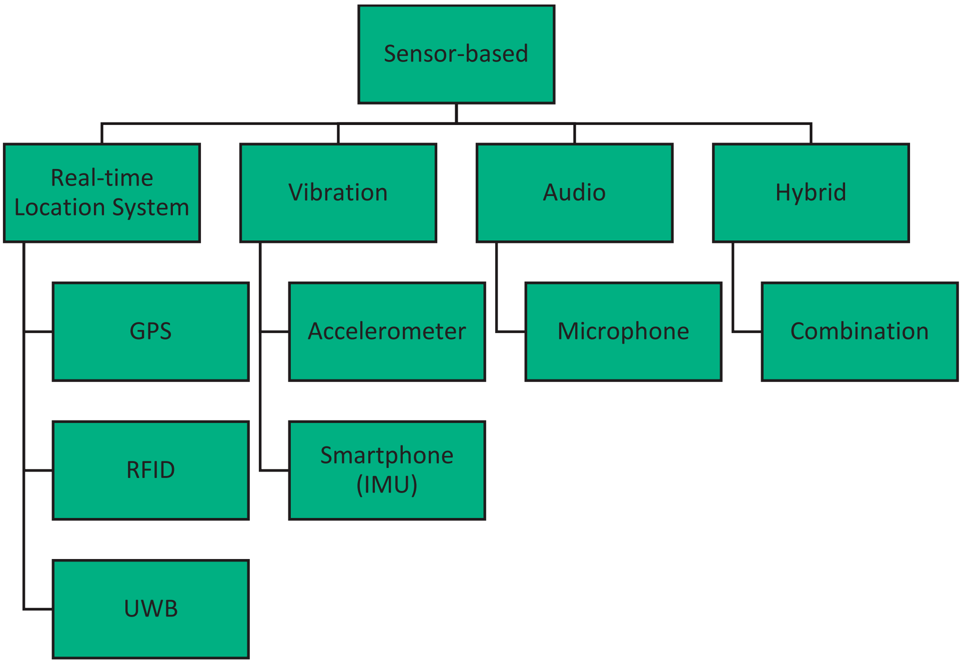


Figure 3. Classification and hierarchy of sensor-based monitoring methods

Computer Vision-based Methods

CV-based methods collect equipment operation data from site surveillance cameras, such as videos or images. The camera's visual data are processed with CV-based methods (e.g., machine learning and deep learning) to identify equipment activity. Finally, based on the activity information, the equipment's productivity can be estimated by equipment operation time or soil quantity (Chen et al., 2022).

A general CV-based equipment monitoring framework consists of several steps. First, equipment detection recognises the equipment in the image or video frames. Next, different pieces of equipment are continuously tracked in all video frames. The detection and tracking methods provide the equipment's spatial position and movement information. Finally, activity recognition and pose estimation are conducted to evaluate the equipment's work states, which are necessary for productivity analysis (Chen et al., 2022). Figure 4 shows the three main approaches to monitoring productivity using computer vision.

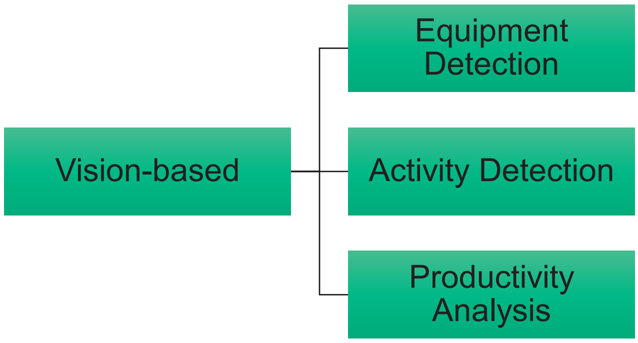


Figure 4. Classification of vision-based systems to monitor equipment productivity

Tables 1, 2 and 3 summarise existing research in the literature. Table 1 summarises the works on equipment detection and tracking. Likewise, Table 2 and Table 3 provide work on equipment activity detection and productivity analysis.

Equipment Detection and Tracking

Table 1. List of various equipment detection methods (Chen et al., 2022)

Detection Methods	Type	References
Feature-based	Histogram of Gradients (HoG) + Support Vector Machine (SVM)	(K. Kim et al., 2017; Rezazadeh Azar et al., 2013; Rezazadeh Azar & McCabe, 2012b, 2012a; Tajeen & Zhu, 2014)
	HoG, colour, hue-saturation + SVM.	(Memarzadeh et al., 2013)
	Colour	(Zou & Kim, 2007)
Gaussian Mixture Model (GMM)	GMM	(Bügler et al., 2014, 2017)
	GMM + Bayes Network	(H. Kim et al., 2016)
	GMM, Bayes Network, CNN	(Chi & Caldas, 2011)
Marker-based	Barcode marker + HoG + SVM	(Azar, 2016)
Tracking-Learning-Detection (TLD)	Trajectory, Spatial and Gray-value variance, Pixel variance	(J. Kim et al., 2018; J. Kim & Chi, 2017)
Convolutional Neural Networks (CNNS)	ResNet-50	(H. Kim, Kim, et al., 2018)
	Faster R-CNN	(Chen et al., 2020; Fang et al., 2018)
	CNN + Long-Short-Term-Memory (LSTM)	(J. Kim & Chi, 2019)
	ResNeXt-101	(Roberts & Golparvar-Fard, 2019)
	Faster R-CNN + Single Shot Detector (SSD) + You Only Look Once (YOLO)	(J. Kim et al., 2020)

Equipment Activity Detection

Table 2. Summary of equipment activity detection methods (Chen et al., 2022)

Method	**Activities**		**References**
	Excavator	**Truck**	
Feature-based	Relocating, excavating, swinging	-	(Gong et al., 2011)
	Digging, hauling, dumping, swinging	Filling, dumping, moving	(Golparvar-Fard et al., 2013)
	Idling, swinging, loading, moving, dumping	Moving, filling, hauling	(Roberts & Golparvar-Fard, 2019)
Rule-based	Idling, stopping	-	(Zou & Kim, 2007)
	Loading	Loading	(Rezazadeh Azar et al., 2013)
	Filling	-	(Bügler et al., 2014, 2017)
	Bulldozer: excavation, spreading; excavator: excavation, trenching, loading; grader: spreading, ditch cutting; roller: compaction	truck: backfilling, loading, hauling, compaction	(Rezazadeh Azar, 2017)
	Dumping, idling	Loading, hauling	(H. Kim, Bang, et al., 2018)
	Idling, travelling, working	Idling, working	(J. Kim et al., 2018)
Convolutional Neural Networks (CNNs)	Digging, hauling, dumping, swinging	-	(J. Kim & Chi, 2019)
	Digging, swinging, loading	-	(Chen et al., 2020)

Productivity Analysis

Table 3. Summary of vision-based works using productivity analysis (Chen et al., 2022)

Method	Activities		Calculate Operation time	Calculate Productivity	Accuracy	References
	Excavator	**Truck**				
Activity Recognition	Idling, stopping		Yes	-	99.8%	(Zou & Kim, 2007)
	Loading	Loading	Yes		95%	(Rezazadeh Azar et al., 2013)
	Filling		Yes	Yes	82.56%	(Bügler et al., 2014, 2017)
	Dumping, idling	Loading, hauling	Yes	Yes	98.4%	(H. Kim, Bang, et al., 2018)
	Idling, travelling, working	Idling, working	Yes		94.6%	(J. Kim et al., 2018)
	Digging, hauling, dumping, swinging		Yes		90.09%	(J. Kim & Chi, 2019)
	Digging, swinging, loading		Yes	Yes	83%	(Chen et al., 2020)
Licence plate recognition		Truck work cycles	Yes	Yes	96.76%	(H. Kim et al., 2019)
Matching cameras		Truck work cycles	Yes	Yes	97.6%	(J. Kim & Chi, 2020)

2.3 Case Studies

In this section, we present five case studies related to productivity monitoring.

Underground Construction Site Monitoring

Researchers (Bügler et al., 2014) used photogrammetry and video analysis to monitor the earthwork productivity of an underground construction site in Munich, Germany (Figure 5). They used photogrammetry images to determine the earth volume excavated and video analysis to produce site statistics, such as loading times, idle times, and relevant project information. Combining the two data sources (photogrammetry and video analysis) allowed the team to measure the machinery productivity and site-specific performance factors.

A video camera positioned atop a tower crane was placed at the site to capture videos of the excavators and dump trucks. Images captured from various perspectives were employed for photogrammetry. The designated location for the study was a recently constructed underground parking facility in a notably restricted section of Munich. The area necessitates a substantial excavation undertaking to be completed before the initiation of primary construction operations.

Figure 5. Excavation site in the downtown area of Munich, Germany (Bügler et al., 2014)

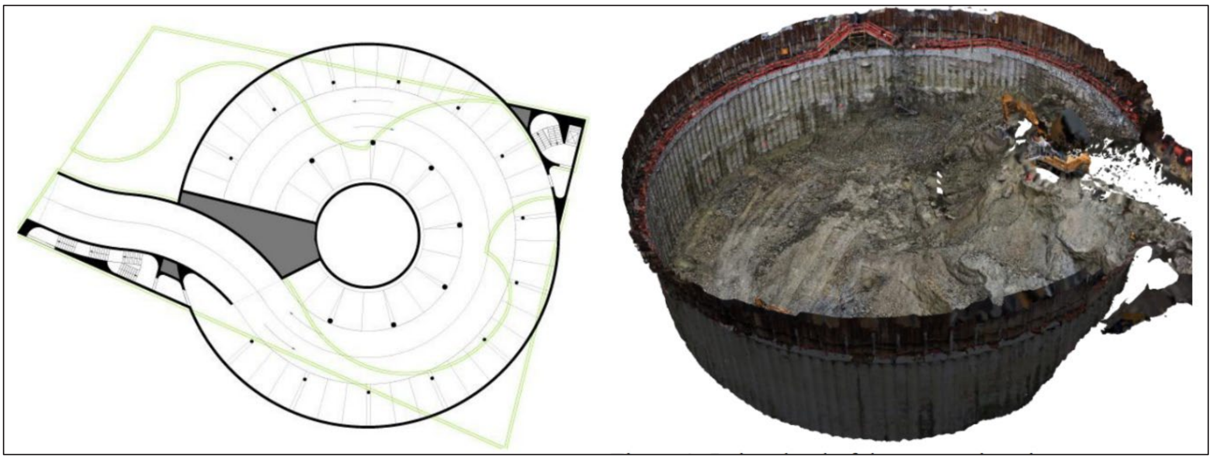


Figure 6. Construction site layout (50 metres diameter) and the corresponding point cloud of the excavation site (Bügler et al., 2014)

Volume calculation Using Photogrammetry

The quantity of excavated soil on an excavation site is measured by creating a 3D point cloud of the site space and using the information to obtain a volume measure. The photogrammetry method utilises images captured by a pedestrian worker using a standard digital camera as the primary data input source. A computer program is utilised to recognise distinctive points in the obtained images using the scale-invariant feature transform (SIFT). These unique features are then tracked across the various images, with those present in at least three photographs enabling the triangulation of points within the 3D space, ultimately culminating in forming a point cloud.

To compute the volume enclosed by the point cloud (Figure 6), a series of sequential procedures must be executed. First, the point cloud is cleaned to eliminate extraneous points lying beyond the excavation zone via cluster analysis. Next, a uniform top plane encompassing the excavation region is determined through marker points or vertical histogram analysis. Finally, the point cloud's volumetric computation is calculated.

Excavation Tracking Using Video

Analysing videos comprises four steps: (1) target identification, (2) target tracking, (3) assessment of activity status, and (4) event detection processing.

Target identification focuses on identifying elements within the image that require tracking. Upon target detection, a kernel covariance tracker is activated to facilitate **target tracking**. Concurrently, the system estimates the **activity status** of each entity, determining if it is moving or stationary. Moreover, the activity status estimator assesses whether an excavator is loading a dump truck. Subsequently, the **event detection** processor integrates tracker and activity status estimator data to produce comprehensive metrics concerning significant on-site occurrences. Figure 7 shows the overview of the approach.

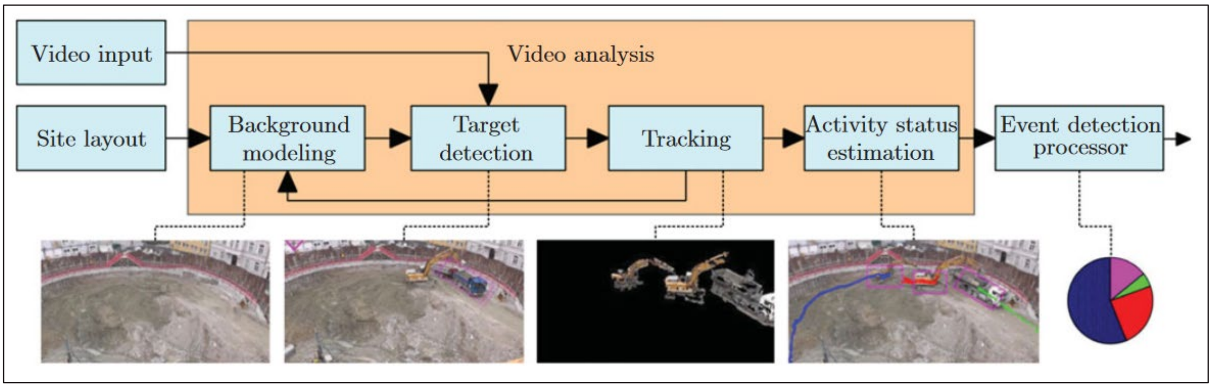
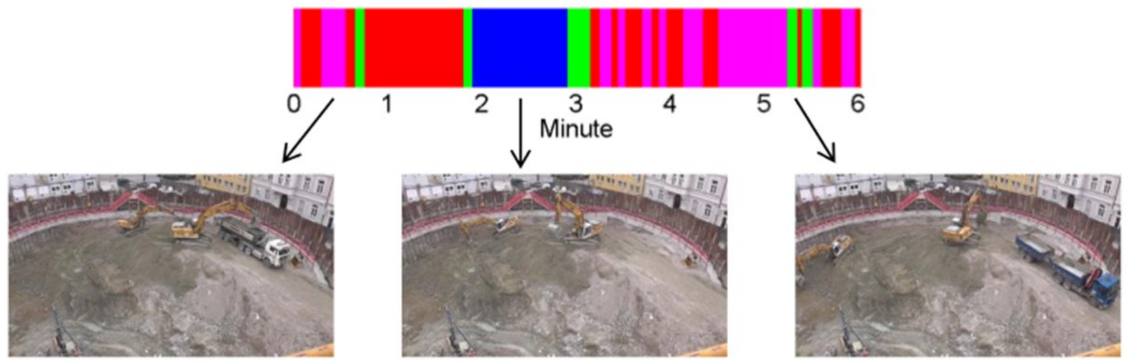
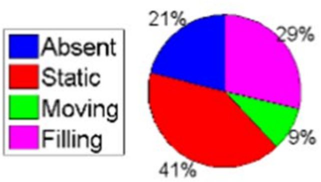


Figure 7. Overview of Video Analysis for Detecting Events (Bügler et al., 2014)

The event detection processor analyses trajectory information from the tracker and the results from the activity status estimator. It will then produce necessary statistics to estimate the duration of the work activities performed by the excavators and dump trucks. The analysis includes the number of dump trucks entering the area, their duration in the region for loading, the quantity of soil loaded in each dump truck, and the idle times of machines on-site. Figure 8 shows the sample dump truck state estimates and the corresponding event analysis.



Dump truck state estimates for a video segment. The activity states are static (red), moving (green), filling (magenta), and absent (blue). Initially a dump truck is in the scene, then leaves (2 minute mark). Another enters (near 3 minute mark) and is then filled by the excavator.



Truck Load (No.)	Entered Site at Minute	Moving (Mins)	Static (Mins)	Filling (Mins)	Exited Site at Minute	Total on Site (Mins)	# of Buckets to Load
3	26.75	0.36	3.2	1.43	31.74	4.99	8
4	32.85	0.59	1.35	2.06	36.85	3.99	9

(a) Sample pie chart

(b) Sample event statistics table

Event analysis and statistics for a video segment. The event processor tabulates the temporal statistics of the activities and also identifies events, such as filling cycles and outlier time spans. For the analysed timespan, the pie chart on the left indicates what percentage of the time was spent engaged in which activity state. The activity states are static (red), moving (green), filling (magenta), and absent (blue). The sample table on the right depicts the activity analysis breakdown based on the frames analysed

Figure 8. Dump truck state estimates and event analysis for a video segment (Bügler et al., 2014)

Productivity of Tunnel Earthmoving

This study (H. Kim, Bang, et al., 2018) integrated construction process simulation and vision-based context reasoning to measure tunnel productivity analysis. An object detector detects excavators and dump trucks in images, inferring the earthwork context. Using the earthwork context, the probability of task duration is estimated. This estimation is fed to the WebCYCLONE simulation. The estimated task durations from the simulation were identical to the actual earthmoving process. Figure 9 shows the overall flow of the approach.

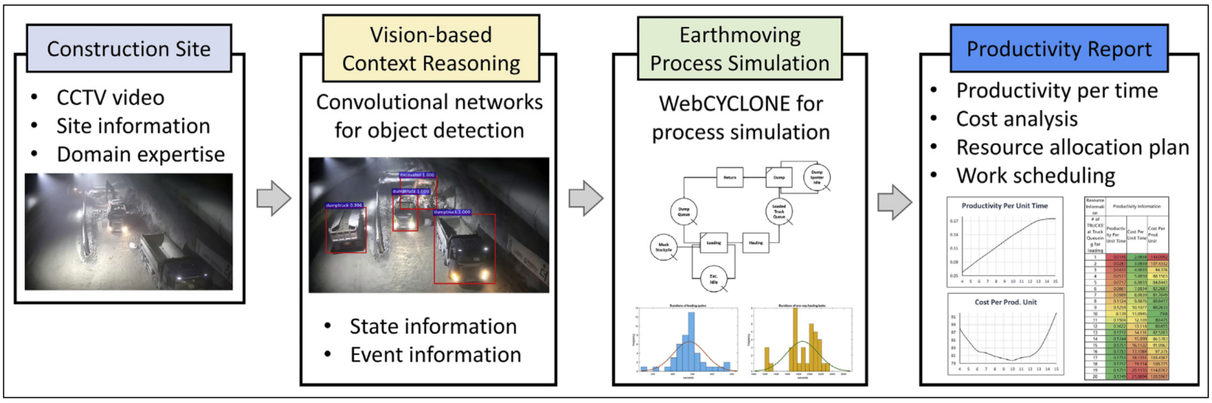


Figure 9. Overview of tunnel earthmoving study (H. Kim, Bang, et al., 2018)

Construction Site

The tunnel is currently being constructed utilising the novel Austrian tunnelling technique (NATM). The targeted earthmoving process involves the transportation of waste derived from excavated materials in a tunnel, including blast rock and soil, through a single excavator and seven dump trucks to the temporary disposal area in the tunnel. It also involves the external aggregate area.

Because this process is not included in the critical path of the NATM process, it is possible to analyse the productivity independently without considering other processes. In a single day, about 680 cubic meters of dirt is generated, and the temporary disposal area can hold up to 1500 cubic meters. The NATM process is needed for 600 days for this tunnel construction, and a single closed circuit television (CCTV) camera keeps an eye on the temporary disposal zone all day. The tunnel videos were recorded at a frame rate of 30 frames per second at the actual tunnel construction site from 7:38 am to 4:49 pm. All video frames were resolutions of 720x480.

Productivity of Loading and Hauling Tasks

The state and event information from images are used to analyse the productivity of an earthmoving task. The state information refers to the state of an earthmoving task, and the event information refers to the start and end times of a cycle of the earthmoving task. The loading task works when an excavator and dump truck are within a certain distance. The state information of each frame is used to identify the start and end of a loading task.

The event information of loading cycles can be used to determine a hauling task's start and end times. Upon recording the loading cycle's completion time, the dump truck's hauling task is initiated. When the dump truck returns to the temporary disposal area, the end time of the hauling task is recorded.

Figure 10 shows the performance of estimating the durations of loading and hauling tasks using the vision-simulation process and actual completion. Figure 11 shows the sample images of the detection of excavators and dump trucks.

	Estimated	Ground truth	Error rate
The number of tasks	44	44	0%
Duration average of loading tasks (unit: seconds)	342.2	336.8	1.6%
Duration average of one-way hauling tasks (unit: seconds)	1869.1	1871.4	0.12%

Figure 10. Performance of estimating the durations of loading and hauling tasks (H. Kim, Bang, et al., 2018)

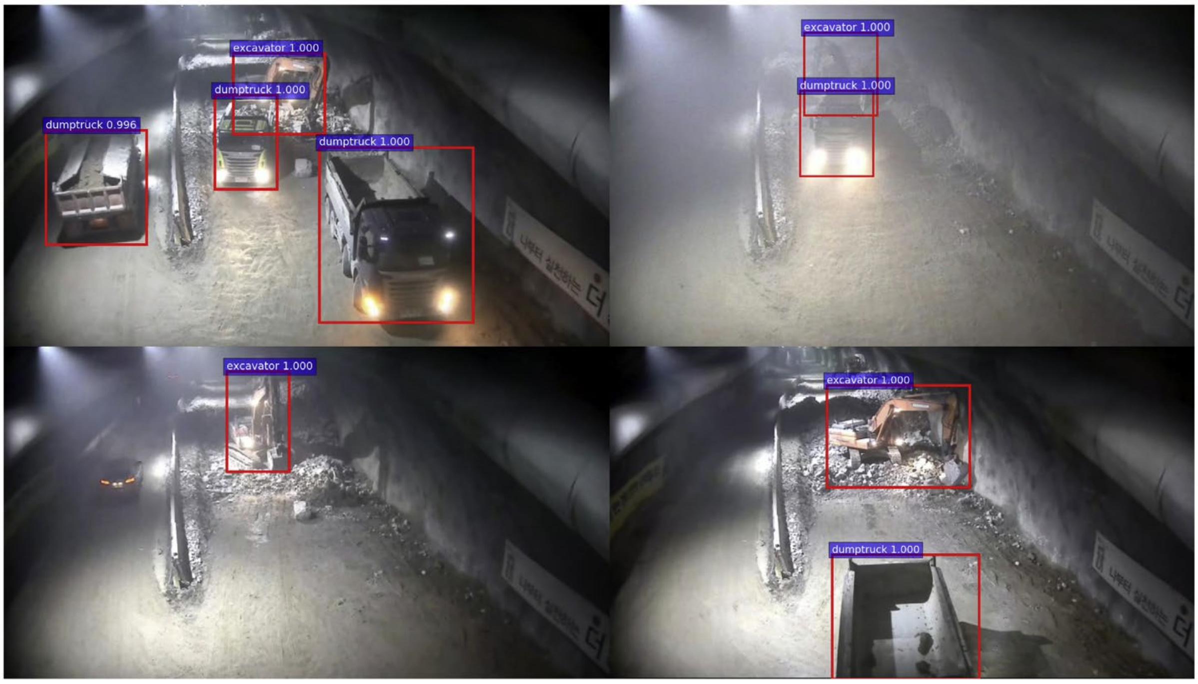


Figure 11. Sample images of excavator and dump trucks from the site (H. Kim, Bang, et al., 2018)

Construction Site Excavation

The study (Chen et al., 2020) focused on measuring the productivity of multiple pieces of equipment and proposed a framework for automatically analysing the activity and productivity of several excavators. CNNs were employed to detect, track, and recognise excavators' activities. In addition, the study compiled the excavator's activity time, working cycle, and productivity. Figure 12 shows the complete overview of the method.

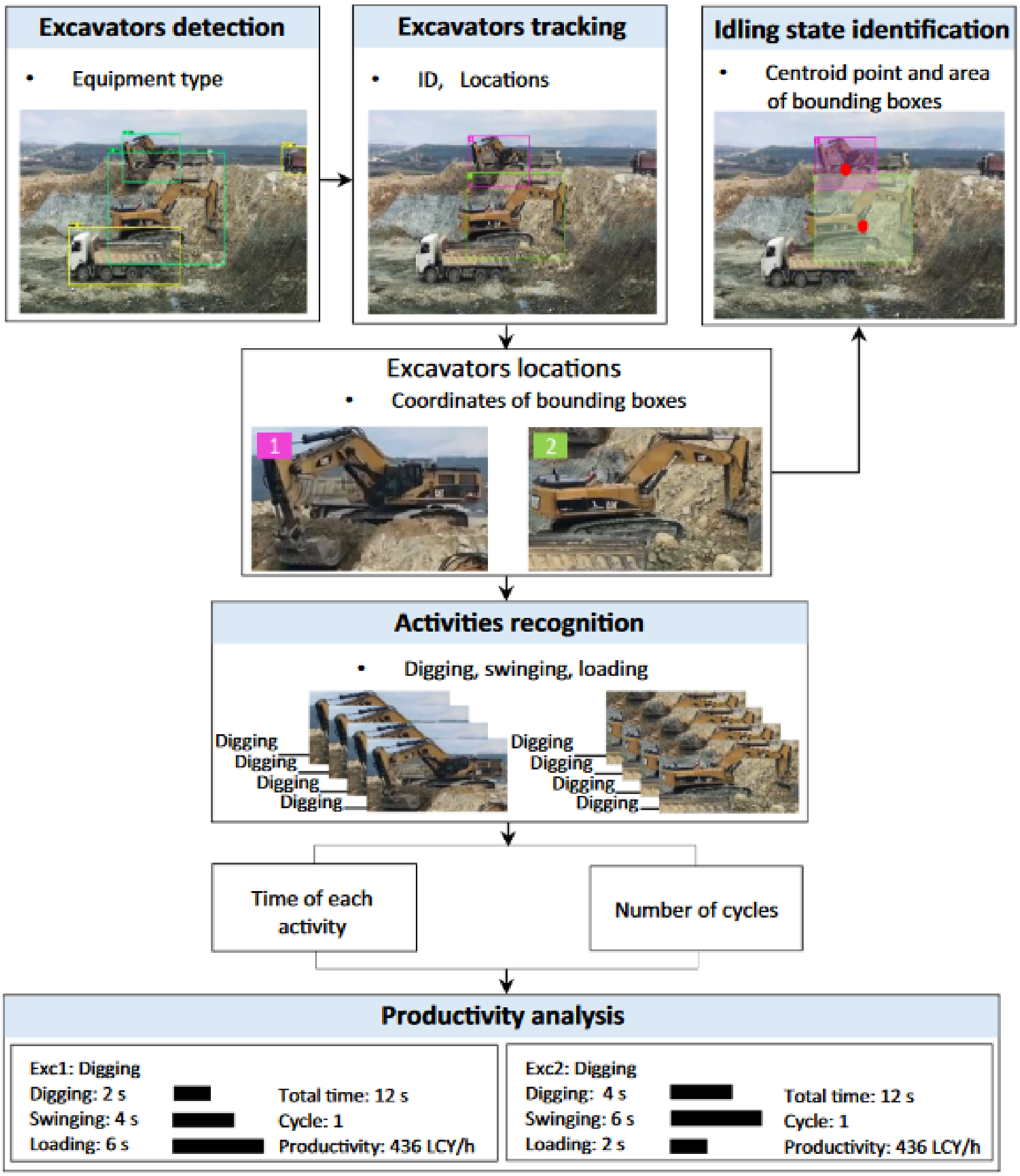


Figure 12. Overview of the proposed approach to productivity analysis (Chen et al., 2020)

Dataset

This study collected 351 video clips from 21 construction sites, considering site conditions, equipment viewpoints, and excavators' scales and colours. Thirty video clips with a resolution of 1280 × 720 pixels and a duration of 264 s were used to test the performance of the activity recognition model. Figure 13 shows the sample images.

Figure 13. Samples images from the dataset (Chen et al., 2020)

Excavator detection and tracking

The framework comprises five major components: excavation detection, tracking, idle state identification, activity recognition, and productivity evaluation. The first step is to use a detector to identify all the excavators in video frames. The detection results provide two data types: equipment type and region. Second, each excavator and its trajectory are tracked through detection-based tracking. The tracking results give an identification number and bounding boxes for each excavator.

In successive frames, the centroid coordinates and areas of the excavators' bounding boxes will alter, revealing idle states. Then, a 3D CNN model is used to identify the activities of the tracked excavators. Based on the results obtained from the activity recognition and idling state identification tests, each video frame is assigned a label accordingly. Finally, the productivity of each excavator is calculated by combining the activity recognition results with the productivity of each excavator.

Activity Recognition and Productivity

In video sequences, a 3D residual neural network (3D ResNet) was used to recognise the excavator's activities (digging, loading, and swinging).

The productivity of the excavator is based on the activity recognition results. The excavator's productivity is calculated with the cycle time and the bucket payload (measured in Loose cubic yards, LCY, per hour) as

$$Productivity\left(\frac{LCY}{hr}\right) = \frac{Cycles}{hr} \times \frac{Average\ bucket\ payload\ (LCY)}{Cycle} \qquad 1$$

Figure 14 shows the activity recognition output, and Figure 15 shows the sample productivity output.

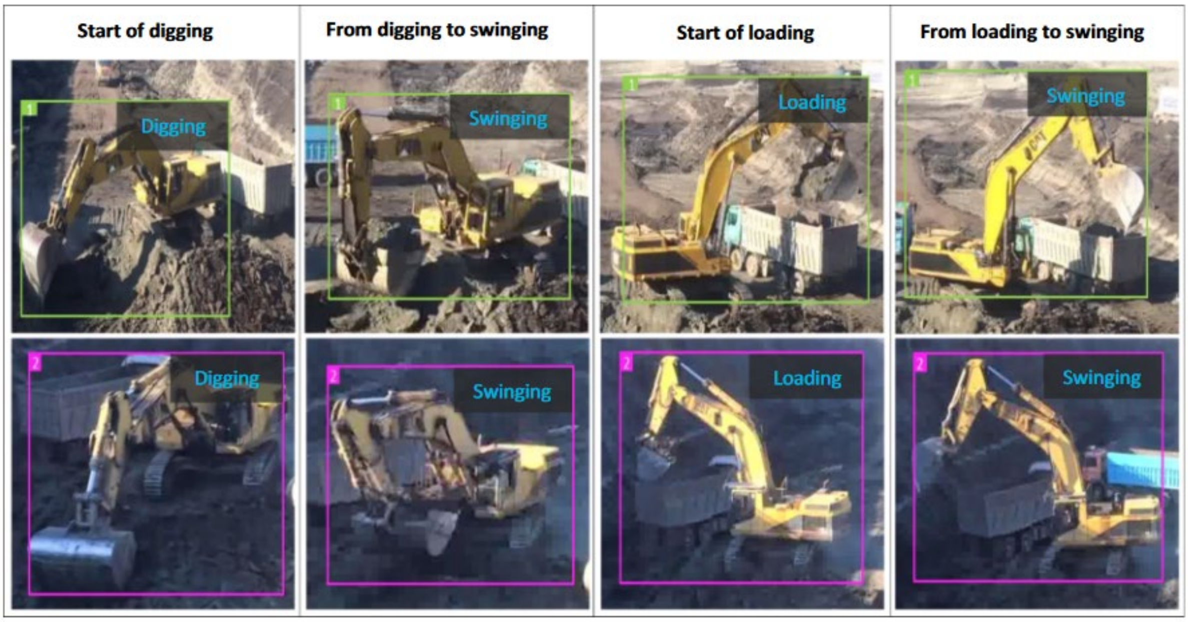


Figure 14: Activity recognition of excavator (Chen et al., 2020).

Figure 15. Example of productivity calculation results (Chen et al., 2020)

Limitations of the work:

The detection and tracking results affect the activity recognition performance. When the bounding boxes of two excavators overlap, the activity of one excavator might be impacted by the activity of the other excavator.

Furthermore, the video's light condition also influences the activity recognition result. When the light is too bright or too dark, it can be challenging to recognise moving features in video frames.

Earthmoving Productivity Simulation Using License Plate Recognition

This study (H. Kim et al., 2019) uses imaging and simulations to present a nonintrusive method for analysing earthmoving productivity. The process involves analysing videos recorded at the entrance and exit of a construction site to deduce earth-moving scenarios using the dump truck site access log. The site access log is automatically generated through a combination of video deinterlacing, a deep convolutional network, and rule-based post-processing, which includes an algorithm for license plate detection and recognition in an unpredictable environment. Simulation-based productivity analysis uses a site access log to generate a daily report, the basis for earthmoving resource planning. Figure 16 shows the overview of productivity analyses using nonintrusive context documentation.

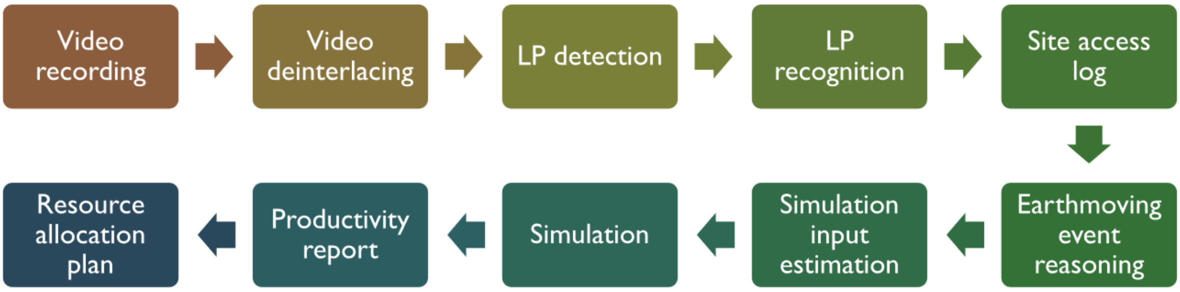


Figure 16. Earthmoving productivity analysis based on the nonintrusive context documentation (H. Kim et al., 2019)

The authors use WebCYCLONE for simulation. Figure 17 shows the construction site entrance and exit, and Figure 18 shows the detection of licence plate numbers from the dump trucks. Figure 18 shows the license plate number detection in sample video frames.

Figure 17. Scenes at the construction site's entrance (left) and exit (right) in the case study (H. Kim et al., 2019)

Figure 18. Licence plate detection in video frames (H. Kim et al., 2019)

Multi-camera Equipment Matching for Productivity Analysis

In this case study (J. Kim & Chi, 2020), researchers propose a multi-camera-based productivity analysis using computer vision, compared to single-camera-based approaches in previous studies. They utilise videos from multiple non-overlapping cameras at the construction site. It includes three main steps: (1) placing multiple cameras at different locations, (2) monitoring equipment based on single-camera video data, and (3) matching the equipment from multiple cameras to assess productivity. The authors used video data of 371,125 image frames from the construction site (highway) to validate their approach to arrive at an average of 97.6% matching accuracy. Figure 19 shows the overview of the proposed approach.

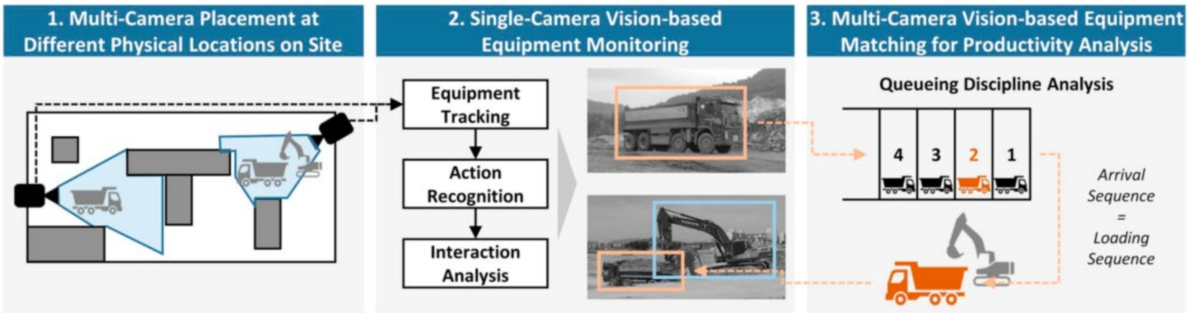


Figure 19. Overview of the proposed methodology for multi-camera vision-based monitoring (J. Kim & Chi, 2020)

Figure 20 shows the operational states of excavators and sump trucks considered in this case study, and Figure 21 shows the process involved in monitoring equipment productivity from a single camera.

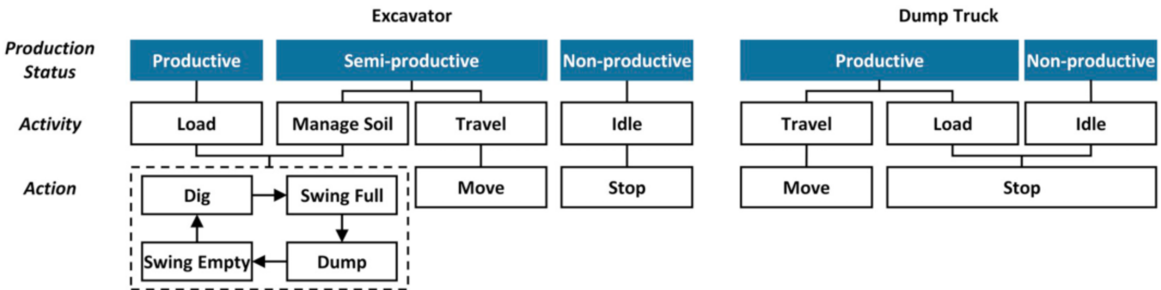


Figure 20. The case study considers the operational states of excavators and dump trucks (J. Kim & Chi, 2020)

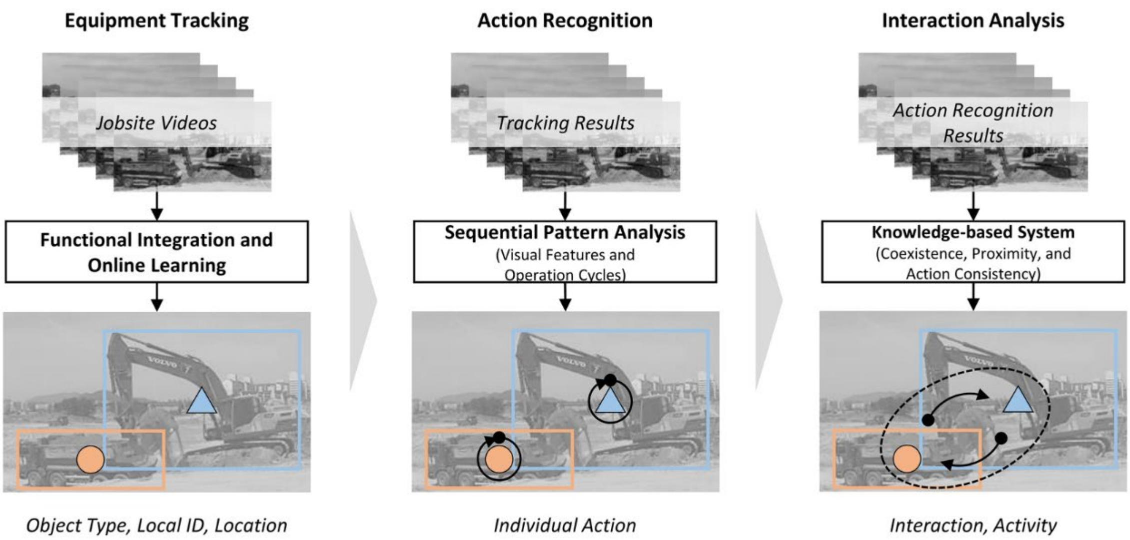


Figure 21. Shows the process of monitoring equipment productivity from a single-camera (J. Kim & Chi, 2020)

The project was undertaken on the Cheonan-Asan highway in South Korea, and the site was approximately 500 m × 600 m. The job site had three loading zones and three entry zones. One excavator was assigned to load soil onto multiple dump trucks in each zone. Figure 22 shows the conceptual layout of the cameras on site and the actual images collected from the site.

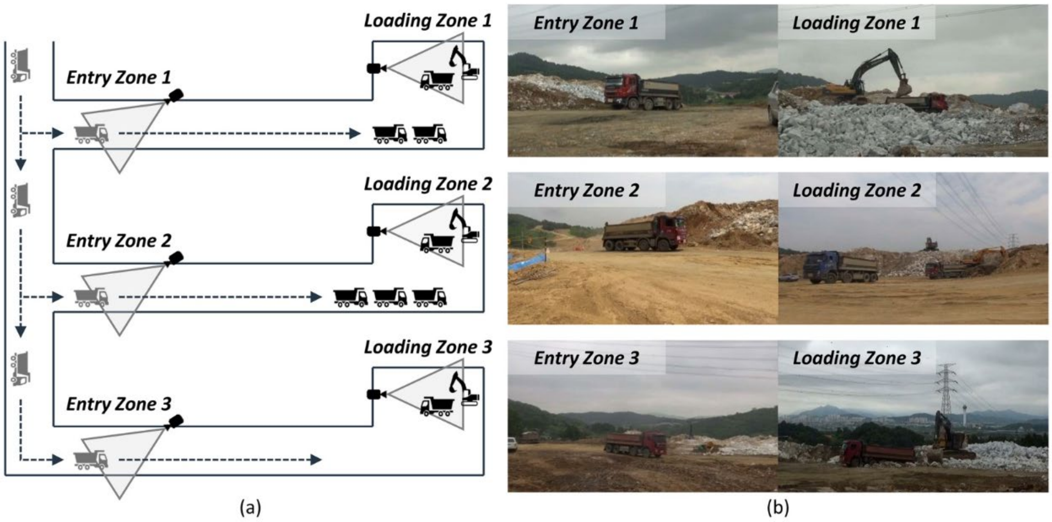


Figure 22. (a) conceptual site layout and (b) images collected from the site (J. Kim & Chi, 2020)

In Figure 23, we can see the results of multi-camera vision-based equipment matching. At the entry zone, two different white trucks (with similar velocities) were captured in the image frames T = 1657 and T = 4257, respectively. The method successfully paired them in the loading zone at image frames T = 8252 and T = 11447 after interacting with the excavator and performing a 'loading' activity in the corresponding service order.

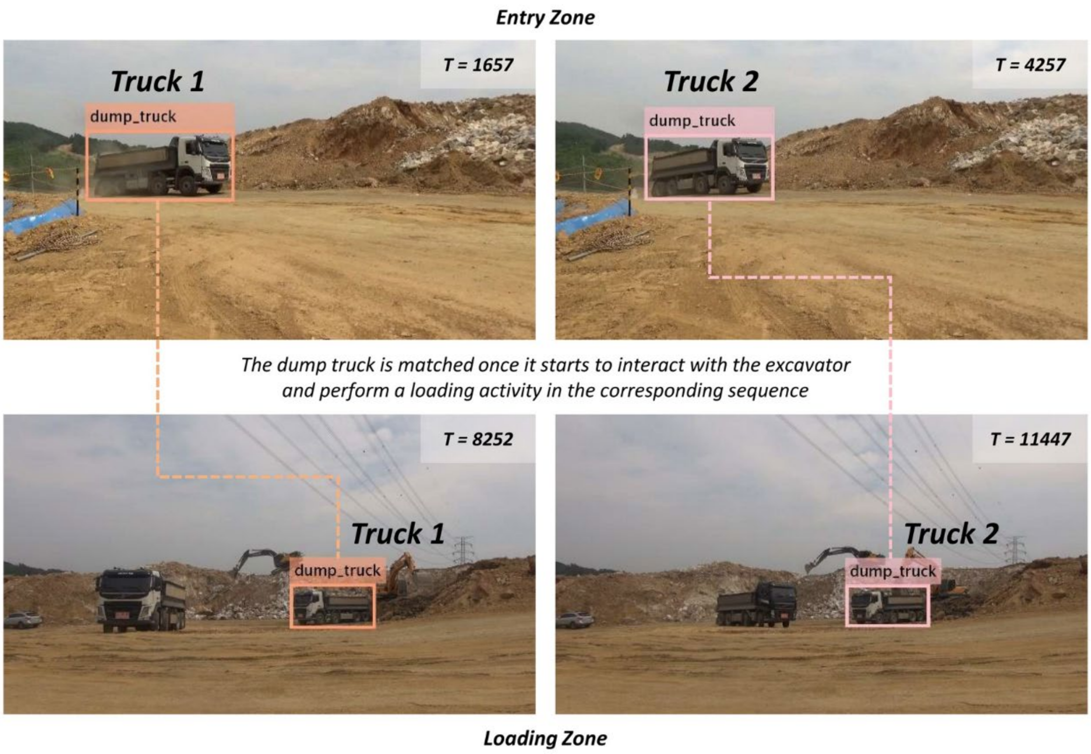


Figure 23. Results of matching the equipment from multiple cameras (J. Kim & Chi, 2020)

Summary of case studies:

In the below table (

Table 4) we summarise the key points from the five main case studies.

Table 4. Summary of case studies reviewed with respect to productivity monitoring

	Focus	Approach	Productivity Analysis	Disadvantages
(Bügler et al., 2014, 2017)	Underground earthwork	Photogrammetry + Video analysis	The volume of soil excavated at regular intervals. Loading, idle times	Rain, snow and difficult light conditions may affect the images
(H. Kim, Bang, et al., 2018)	Tunnel	Construction-process simulation + Vision-context reasoning - WebCYCLONE simulation	• Number of dump trucks • Process cycle per hour. • Muck removal per hour. • Muck removal per day. • Idle time for an excavator • Idle time for dump trucks • Rental cost per day • Unit cost ($/m^3)	Only the muck transportation process was analysed. Equipment combinations, geologic properties, and the entire tunnelling process are not considered
(Chen et al., 2020)	Construction site	Faster-RCNN+Deep SORT tracker + 3D ResNet Classifier Uses centroid	• Activities of multiple excavators are used • Productivity is analysed using LCY per year.	Cannot distinguish between overlapping excavators. Lighting conditions Limited data diversity
(H. Kim et al., 2019)	Construction site	Videos and Simulation License Plate Recognition	Analysing videos recorded at the entrance and the exit. The site access log of dump trucks to infer the earthmoving context. - WebCYCLONE simulation	Idle times of excavators and dump trucks account for 34% and 41%. Object detection does not consider geometric properties. Needs re-training when new equipment is introduced
(J. Kim & Chi, 2020)	Highway construction	CNN-Double Layer-LSTM + Knowledge-based rule Multi-camera + Queue system	Dump trucks: • Loading time • Idling time • Inter-arrival time • Cycle time	May fail to track heavy equipment because of background clutter, no-target objects, occlusions, etc. Switch IDs during tracking.

3. EXISTING PRODUCTIVITY METRICS

3.1 Productivity data requirements

The section on productivity data requirements is of the utmost importance in our report, as it establishes fundamental metrics, including production rate, productivity, performance, and exemplar. These metrics serve to direct our examination of crew efficiency. The need of data collection to improve tracking and analysis on-site is emphasised, and it is explained how productivity is monitored on a per-shift basis for each crew. The purpose of this data is multifaceted: it facilitates the identification of exemplary performance, facilitates the comprehension of downtime causes, assesses the influence of communication, furnishes an unambiguous depiction of productivity, assists in forecasting, and guarantees personnel uninterrupted work. This section establishes the fundamental basis for optimising performance and establishing informed decisions to increase productivity and efficiency on construction project.

Definitions[1]:

- Production rate: the total amount of work that is finished in a certain amount of time.
- Productivity: this metric tracks how well the crew is doing by looking at how much work they get done each shift.
- Performance: calculated by adding up the resources that were planned and the ones that were used.
- Exemplar: the very best work done on a certain task.

Productivity Data Tracking Objectives

On its construction sites, LXRP places a high priority on monitoring their progress and increasing their productivity. The importance of this point cannot be overstated because productivity has a direct impact on the scheduling, expenses, and results of a project. LXRP can obtain considerable insights into the efficiency with which resources are utilised by crews and shifts by monitoring crucial indicators such as production rate, productivity, performance, and exemplar work.

LXRP adheres to the Planning Objective DARUPTO to accomplish continuous improvement, which covers the following categories (Level Crossing Removal, 2023):

- **D**esign: Ensuring that a consistent design is implemented, which will allow teams to perform continuous repetitive labour.
- **A**ccess: Ensuring that all work locations are accessible without boundaries.
- **A**pproval: Acquiring all the essential approvals and permits, including the ability to govern the circumstances that were generated by stakeholders in closer proximity.
- **A**vailable: Ensuring that resources such as dependable production equipment and skilled labour are readily available.
- **R**elocation: All utility services will be safeguarded, and any necessary modifications or relocations will be made to them.
- **U**nsuitable: Protection of susceptible surfaces that are exposed to weather, streamflow, and ground conditions, as well as control of situations that are not acceptable.
- **P**rocurement: Implementing procurement arrangements that incentivise greater productivity.

[1] HIVE Research & Development (2023)

- **T**raffic: Managing traffic for haul roads on-site and routes off-site.
- **O**ut-of-sequence: Getting rid of work that is performed out of sequence.

When it comes to enhancing productivity tracking and analysis on construction sites, the data that is collected throughout this monitoring process is both valuable and beneficial. There are many important roles that it plays. The first benefit is that it makes it possible for LXRP to identify instances of extraordinary performance, thereby providing a benchmark for the most efficient output. This technique for benchmarking serves the purpose of establishing benchmarks for the highest possible levels of output that crews are capable of achieving (HIVE Research & Development, 2024a).

Second, the data makes it possible for LXRP to better understand the factors that contribute to periods of inactivity or inefficiency, which in turn enables the project team to make adjustments that are more specific. Through the process of assessing the ways in which communication and coordination methods impact production, LXRP can implement targeted initiatives that will increase overall efficiency.

In addition, the data that was collected provides a clear picture of the productivity that was achieved under actual site conditions. All of the people who are participating in the project can benefit from this knowledge since it enables them to comprehend the levels of productivity that have been achieved and the factors that have an effect on those levels.

As an additional benefit, the data on productivity makes it possible for planners, schedulers, and estimators to properly forecast the productivity of crews under situations that are comparable. By doing so, the accuracy of project planning is improved, and it guarantees that resources are utilised in an effective manner.

Last but not least, productivity data ensures that crews have regular, repetitive work, which ultimately leads to an increase in productivity levels. This is accomplished by providing feedback to the design team. The existence of this feedback loop makes it possible to continuously enhance and optimise the use of resources throughout the lifecycle of the project.

In general, the thorough data collection and analysis process that LXRP employs as a base serve as a foundation for enhancing productivity, improving project outcomes, and ensuring resource efficiency on construction sites.

3.2 Benchmarking Procedure used in LXRP

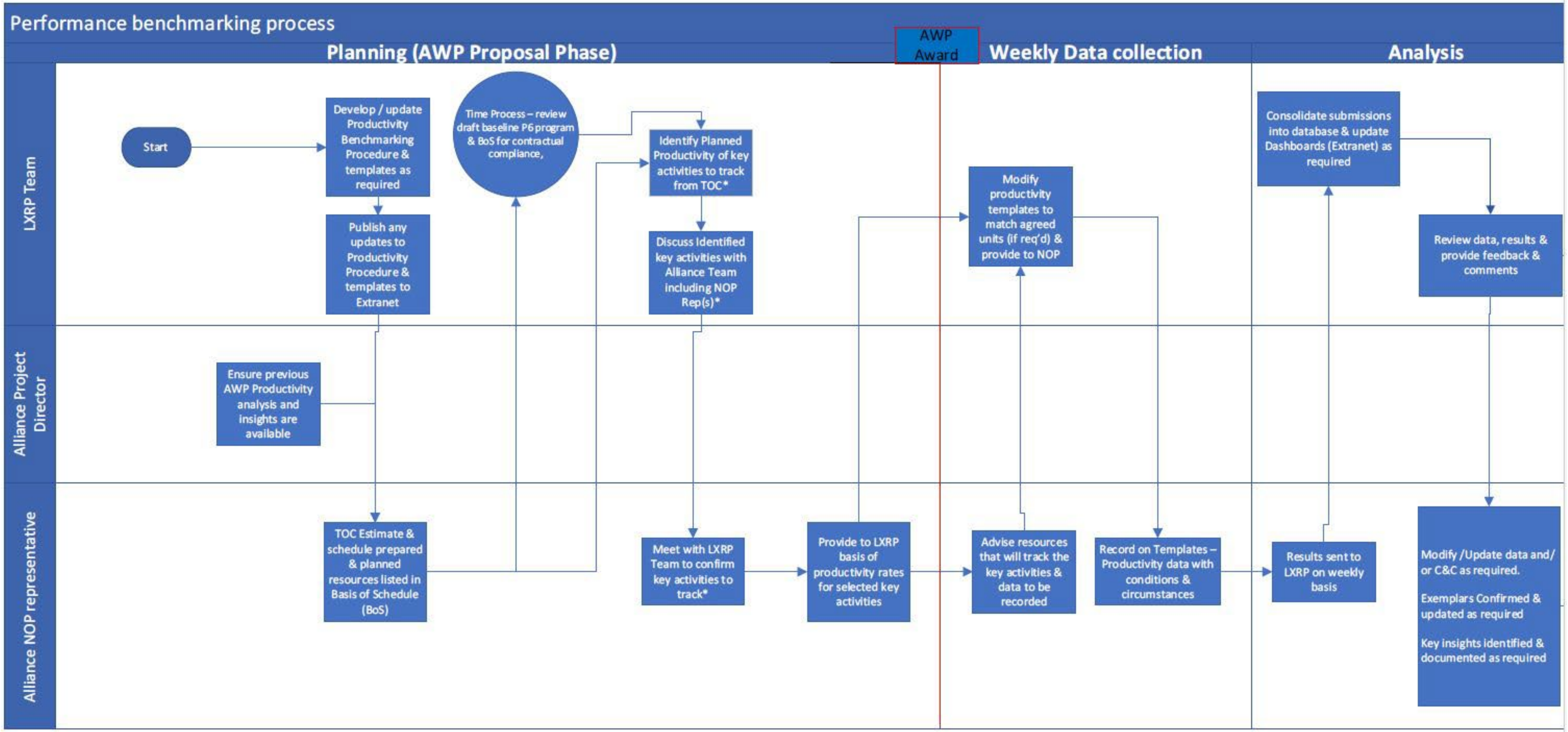


Figure 24. Productivity Benchmarking Process Flowchart (Appendix B) (Level Crossing Removal, 2022)

LXRP's Productivity Benchmarking Process is a comprehensive, five-step procedure aimed at enhancing the efficiency and effectiveness of key construction activities within its projects. The process commences with the establishment of consensus on the Key Activities to monitor, which are selected based on their significant impact on the Alliance Work Package (AWP) and their potential for continuous improvement due to their repetitive nature over prolonged periods.

The next phase involves the meticulous gathering of planned resources data for Plant, Labour, and Materials (PLM), alongside expected productivity rates for these Key Activities. This planning stage is critical as it establishes a baseline for performance measurement, providing a reference point against which actual productivity can be evaluated.

As the project unfolds, LXRP rigorously tracks the actual usage of resources, documenting the achieved productivity rates in various conditions and circumstances. This enables the accurate assessment of resource efficiency and the identification of any discrepancies from the initial productivity projections.

Key to this process is the identification of exemplar performances—instances of optimal productivity—which, alongside the analysis of any variances between planned and actual outcomes, offer a comprehensive understanding of productivity dynamics. This step is crucial for recognising best practices and conditions that lead to high productivity, with the intention of replicating these successes in current and future projects.

The culmination of the process is a strong emphasis on the sharing of knowledge. Insights from the benchmarking activities are shared widely, ensuring that successful strategies are communicated and leveraged across teams and projects. This collaborative ethos underpins LXRP's continuous monitoring and refinement approach, which is integral to the AWP's success.

To facilitate this data-driven process, critical documentation is required to inform anticipated productivity rates and resource allocations. The Contractor’s Work Method Statement, the Alliance Program & Basis of Schedule (BoS), and the Construction Management Plan are foundational documents that detail how resources are proposed to be utilised, the scheduling of Key Activities, and the overarching construction methodology and stakeholder management plans.

As Key Activities get underway, Alliances undertake the responsibility of weekly data reporting. They document the actual work completed, resources used, and the conditions and circumstances of their deployment as per the structured framework provided in Appendix E. This regular documentation feeds into LXRP's main goal of establishing normalised productivity rates across projects, serving multiple critical functions: it aids in identifying the most effective methodologies, supports the calculation of the Cumulative Furthermore, it enriches a centralised database accessible to all Alliances and informs LXRP's responses to external inquiries.

Through this diligent and collaborative process, LXRP not only measures but also aims to continually enhance productivity. The benchmarking process is a loop of performance enhancement that is data-driven and founded on a shared commitment to achieving excellence in productivity.

Table 5. LXRP Productivity metrics (Level Crossing Removal, 2022)

No.	Phase	Data Type	Specific Data Collected	Purpose
1	Planning / Pre-Award Phase	Plant Resources	• Plant, Labour, Materials specifics. • Expected productivity rates per resource.	To establish baseline productivity metrics and resource allocation for project planning.
		Project Plans	• Construction Management Plan • Alliance Program & Basis of Schedule (BoS) • Contractor's Work Method Statement	To inform the proposed order and method of work and resources for Key Activities.
2	Delivery / Post-Award Phase	Actual Performance	• Actual Quantity of work per crew per shift • Actual Resource hours used (Plant and Labour) • Materials used	To monitor and track actual resource usage against planned metrics for performance assessment
		Conditions & Circumstances	Environmental and operational conditions affecting productivity	To analyse the impact of various conditions on productivity and adjust future planning accordingly
		Productivity Changes	Comments on changes in productivity from prior periods and their drivers	To identify trends and causes of productivity fluctuations for continuous improvement.
3	Reporting / Analysis Phase	Performance Variances	Differences between planned and actual outputs, resource usage, and productivity rates	To identify and analyse deviations from planned productivity, facilitating targeted improvements.
		Detailed Conditions	Comprehensive recording of Conditions and Circumstances under which the work was performed	To ensure accurate representation of productivity metrics under specific conditions for better benchmarking.
4	Data Submission	Weekly Data	Data submitted weekly via productivity templates	To maintain ongoing records and facilitate timely analysis of productivity data.
		Final Insights	Review of what worked well, what could be improved, and what was missing after each Key Activity	To share key insights and exemplary performances that could guide future projects.
5	Continuous Improvement	Dashboard Data	Data compiled and analysed, presented on various dashboards	To visualise and communicate productivity insights across the program for strategic decisions.
		Trend Insights	Observations on patterns and trends across different projects and conditions	To leverage data-driven insights for enhancing productivity and implementing best practices across projects.

3.3 Current Challenges and Limitations

In the field of construction management, particularly in excavation operations, the reliance on traditional manual data collection methods presents significant limitations and challenges that critically impact project outcomes. These methods, heavily dependent on manual data entry and observation, are fraught with potential for human error. Such susceptibility introduces considerable inaccuracies in records and reports, skewing productivity assessments and complicating effective decision-making. These errors not only affect immediate operational decisions but also have long-term implications on project planning and resource allocation.

The manual process of observing and reporting data is characterised by several inefficiencies. It is notably resource-intensive, requiring a substantial commitment of human labour, which in turn increases operational costs. The need for extensive manpower to track, record, and verify data in real-time—or as close to real-time as possible—places a considerable burden on the project's budget and logistical planning. Moreover, the laborious nature of manual data collection contributes to its time-consuming aspect. Personnel need to be continuously present to monitor activities and record data, a process that is both slow and susceptible to human fatigue, which can further degrade the quality of the data collected.

This method inherently lacks the capability to deliver data in a timely manner. Reports generated manually often experience delays in compilation and dissemination, leading to outdated information that guides critical project decisions. These delays can disrupt project schedules, potentially leading to cascading delays in project milestones and the inefficient use of resources. Additionally, the integrity and auditability of manually collected data are often questionable. The manual entry and observation processes are prone to subjective interpretations and bias, which can alter the data recorded. This subjectivity makes it difficult to maintain consistent quality control and complicates the auditing process, as data verifiability becomes an issue.

In the interview, the site team responded that tracking equipment types and operational times manually is particularly challenging. This process involves monitoring which equipment is in use and for how long, which is crucial for efficient resource management. However, manual tracking is prone to errors, such as misidentification of equipment or incorrect logging of operational hours, resulting in inaccurate assessments of machine utilisation and operational efficiency (Brett Long, 2024).

In response to these challenges, there is a pressing need in construction management to adopt more sophisticated data acquisition techniques. The shift towards automated data collection methods is increasingly seen as a solution to enhance accuracy, reduce labour costs, and provide real-time or near-real-time data. Automation in data collection can include the use of computer vision technologies that continuously collect and transmit data, reducing human error and bias. These technologies not only streamline data collection processes but also improve the timeliness of data reporting, enabling more dynamic and responsive project management. Ultimately, resolving the inefficiencies of manual data collection is crucial for enhancing the overall efficacy and efficiency of construction projects, leading to better managed, on-schedule, and within-budget project completions.

4. DUBLIN ROAD TRIAL

4.1 Project Overview

Figure 25. Dublin Road early concept designs (Victoria's Big Build, 2022)

The project aims to enhance safety, increase train frequency, and improve road network reliability by removing the level crossing at Dublin Road in Ringwood East. The removal of the boom gates will facilitate smoother and safer travel for pedestrians and road users alike.

Key Components:

- Rail Trench Construction: To eliminate the level crossing, a rail trench will be constructed under Dublin Road. This infrastructure improvement will allow for uninterrupted flow of road traffic over the railway line.
- New Ringwood East Station: Alongside the trench construction, a brand-new Ringwood East Station will be built to better serve the community and accommodate increased passenger capacity.
- Upgraded Parking Facilities: The project includes the expansion of car parking facilities, with around 460 upgraded parking spaces planned. This expansion aims to support increased usage and accessibility to the station.

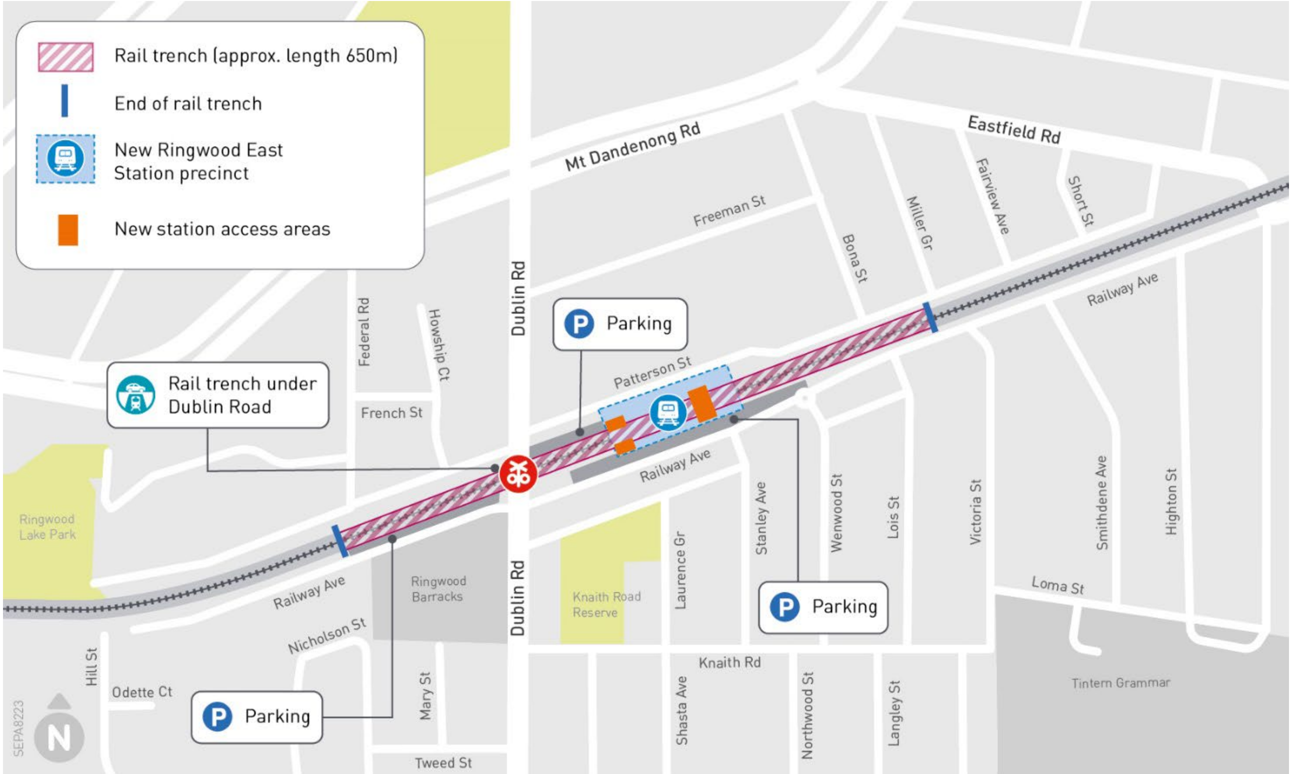


Figure 26. Map of Dublin Road, Ringwood East level crossing removal area (Engage Victoria, 2022)

Computer vision goals in for Dublin Road:

The primary goal for the Dublin Road LXRP is to measure the LXRP productivity metrics using automated data collection methods combined with AI. This innovative approach aims to continuously monitor the volume and rate of earth removal, allowing for real-time assessment against project timelines and productivity targets. By dynamically optimising resource allocation and methods, we expect to gather accurate data and improve reporting efficiency for the construction of the rail trench under Dublin Road in Ringwood East. Additionally, computer vision algorithms will be utilised to monitor equipment usage, ensuring optimal operation of machinery such as excavators, dump trucks, and bulldozers, thus reducing idle times.

Automated productivity reports generated from visual data will enable quick decision-making and facilitate continuous improvement in earthwork operations. The ultimate goal of this integration of advanced technology is to replace conventional productivity reporting methods with real-time and reliable insights from the site. This shift aims not only to maintain high operational standards but also to enhance coordination between earthwork activities and other site operations, ensuring the project adheres to scheduled timelines and achieves efficiency gains.

4.2 Automated Data Collection Motivation

The motivation for automated data collection using computer vision in construction projects is driven by the need to increase efficiency, accuracy, reliability and time between recording data and being able to analyse and view for the construction site. Traditional methods of data collection, typically manual, are often time-consuming, error-prone, and limited in providing real-time insights, frequently taking weeks between data being recoded and being accessible to the project management team. Integrating AI-driven computer vision technology aims to transform this approach by enabling the automation of tracking and analysing machinery movements, usage rates, and overall tool utilisation.

Automated data collection offers continuous, real-time monitoring, which is crucial in dynamic project environments where conditions can swiftly change. This high level of surveillance guarantees more accurate data, available instantly for making informed decisions. AI's ability to recognise various tools and machinery streamlines maintenance planning and resource deployment, enhancing productivity and reducing downtime. Additionally, computer vision provides detailed analytics on equipment performance, aiding project managers in optimising workflows and improving operational efficiency.

Moreover, the automated data collection method powered by AI has the potential to generate metrics and insights not currently available through conventional methods and manual recording and reporting of productivity. The forthcoming study will compare these automated methods to traditional manual data gathering, highlighting the precision, cost-effectiveness, and operational enhancements achievable with this advanced technology.

Table 6. Motivation and benefits of automated data collection through computer vision

Aspect	Benefits of Automated Data Collection
Accuracy and Reliability	Automated systems improve data collection precision, reducing human errors common in manual methods. Accuracy of earth volume removal (counting truck and bucket swing)
Efficiency and Reporting Time	Provides real-time monitoring and analytics, allowing for swift adjustments and decision-making. This real-time data provides insight into potential clashes and inefficiencies, enabling proactive management and timely interventions to prevent delays or issues. Compared to current weekly reporting – Collecting data on a weekly basis does not allow for rapid responses to emerging issues
Deployment	Streamlines scheduling and resource allocation, reducing equipment downtime and optimising productivity.
Operational Improvements	Offers detailed insights into equipment usage patterns, supporting better workflow and operational efficiency. For example, plant that is underutilised could be easily identified and re-deployed on other more critical tasks.

4.3 Existing Data Collection Methods

There are a number of variables and processes that can influence the manual data collection and reporting for LXRP. Manually documenting work quantity, plant and labour hours, and utilisation conditions, alliances are obligated to report on the productivity of resources utilised per crew per shift. Plate-number-recorded dump vehicle movements are utilised as the foundation for earthwork removal productivity metrics. The on-site project manager is provided with manual records of the IN and OUT times, as well as the vehicle type, which are maintained by CYCON employees (Spotters). Site engineers complete the tracking spreadsheet (Appendix A) after receiving a digital copy of the IN and OUT records in Figure 28 from the manager.

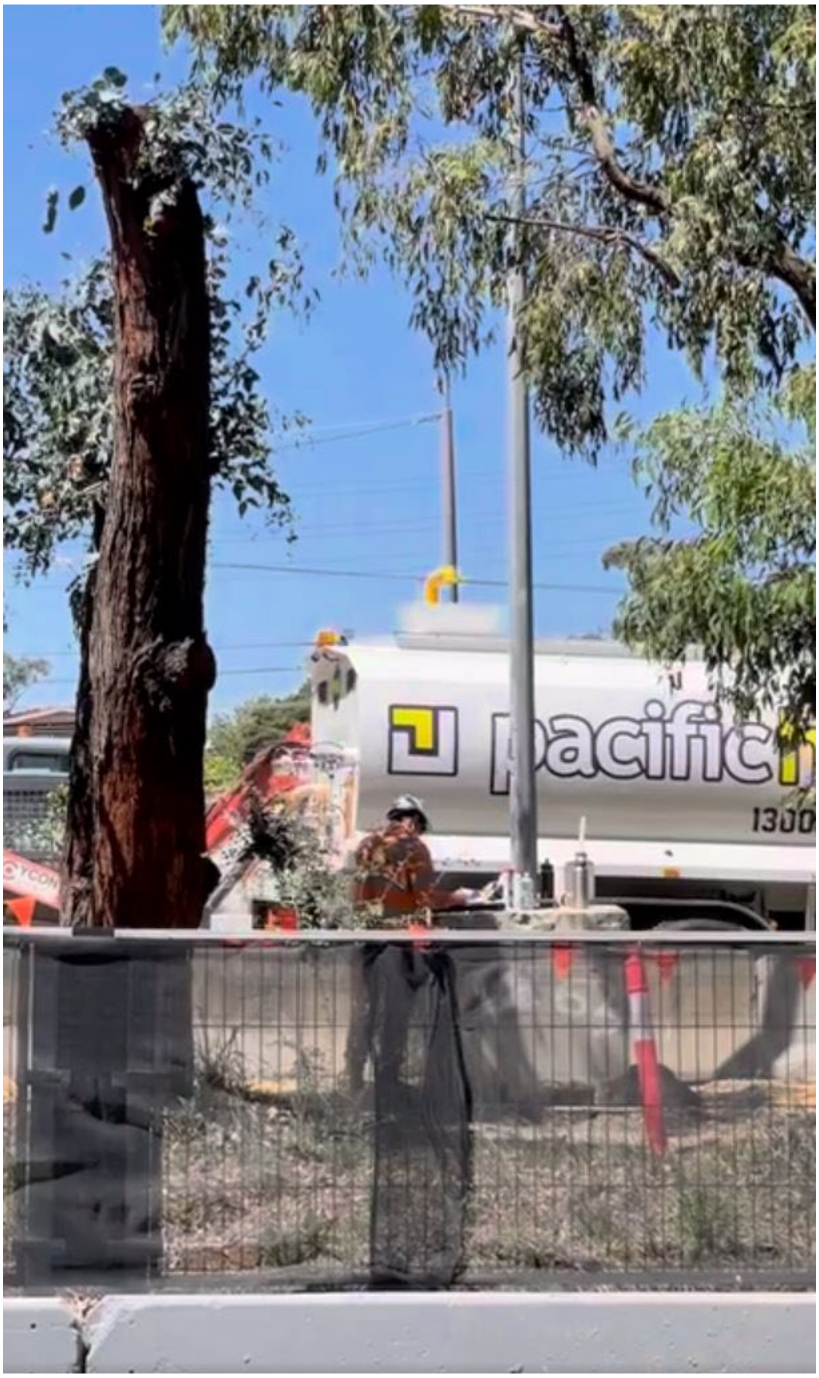
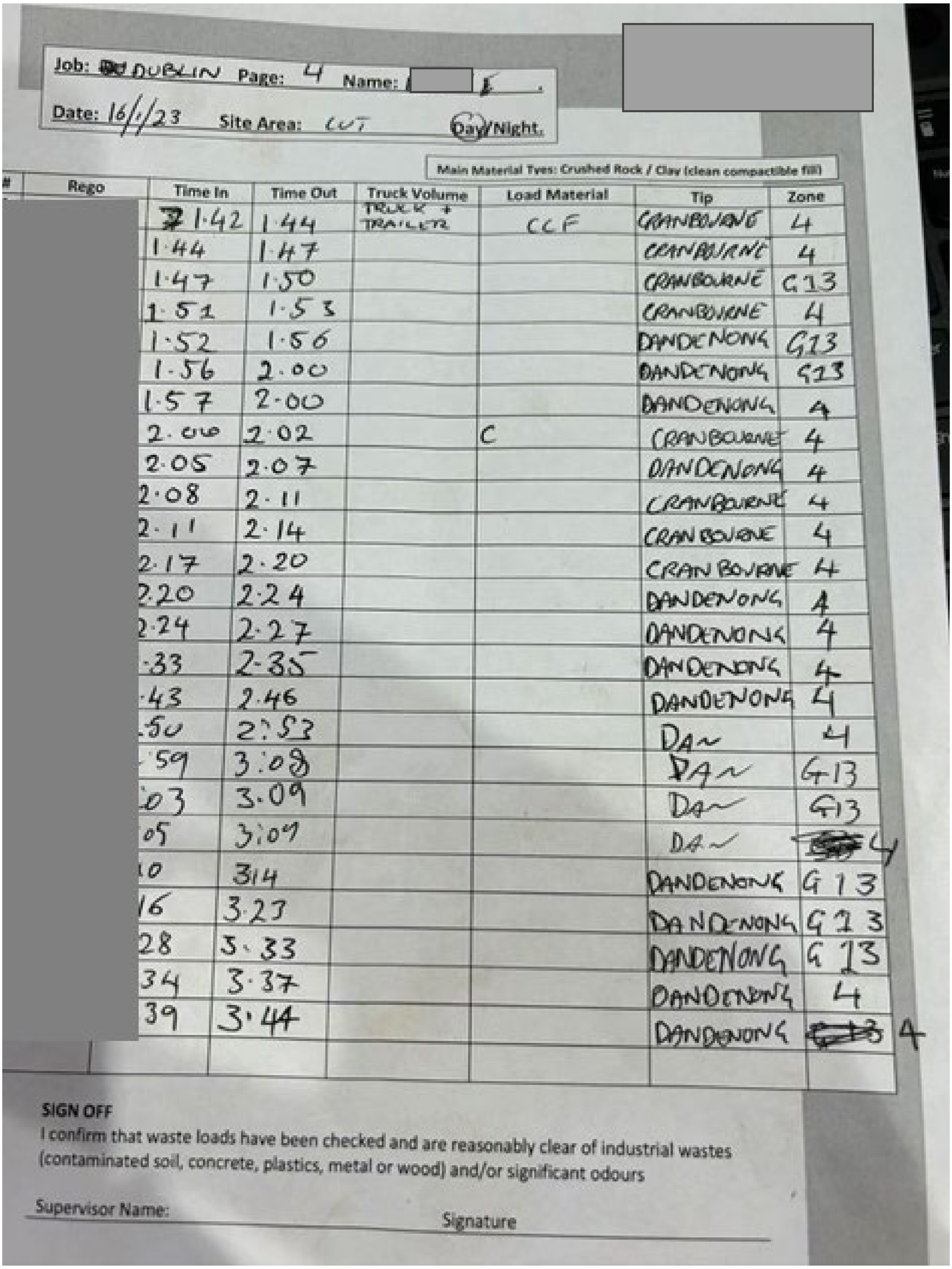


Figure 27. Spotters record Truck + Trailer In and Out the site



[redacted]

Job: DUBLIN Page: 4 Name: [redacted]

Date: 16/1/23 Site Area: CUT Day/Night.

Main Material Tyes: Crushed Rock / Clay (clean compactible fill)

#	Rego	Time In	Time Out	Truck Volume	Load Material	Tip	Zone
	[redacted]	1.42	1.44	TRUCK + TRAILER	CCF	CRANBOURNE	4
		1.44	1.47			CRANBOURNE	4
		1.47	1.50			CRANBOURNE	G13
		1.51	1.53			CRANBOURNE	4
		1.52	1.56			DANDENONG	G13
		1.56	2.00			DANDENONG	G13
		1.57	2.00			DANDENONG	4
		2.00	2.02		C	CRANBOURNE	4
		2.05	2.07			DANDENONG	4
		2.08	2.11			CRANBOURNE	4
		2.11	2.14			CRANBOURNE	4
		2.17	2.20			CRANBOURNE	4
		2.20	2.24			DANDENONG	4
		2.24	2.27			DANDENONG	4
		.33	2.35			DANDENONG	4
		.43	2.46			DANDENONG	4
		.50	2:53			DAN	4
		.59	3:08			DAN	G13
		:03	3.09			DAN	G13
		05	3:07			DAN	~~G13~~ 4
		10	314			DANDENONG	G13
		16	3.23			DANDENONG	G13
		28	3.33			DANDENONG	G13
		34	3.37			DANDENONG	4
		39	3.44			DANDENONG	~~G13~~ 4

SIGN OFF

I confirm that waste loads have been checked and are reasonably clear of industrial wastes (contaminated soil, concrete, plastics, metal or wood) and/or significant odours

Supervisor Name: Signature

Figure 28. Truck IN & OUT Records

Table 7. Data collection example activity – Secondary plant supporting load-out excavator

Metrics Captured	Explanation
Work Done: 854.3 Bm3	The volume of earth moved, or work completed by the secondary plant.
Hours Worked: 7.5	The total number of hours the secondary plant operated for this activity.
Delay: 4.5 hours	The duration of delays encountered, specifically due to unsuitable weather conditions.
Start Date/Time: 10/02/2024 07:00	The date and time when the activity started.
Finish Date/Time: 10/02/2024 14:30	The date and time when the activity finished.
Uptime: 7.5 hours	The actual productive time, excluding delays.
Crew: Crew 1	The team assigned to perform the activity.
Work Zone: Zone 5	The specific area where the activity was carried out.
Location: OTR	The general location or segment of the site where the activity took place.

Explanation of Metrics:

- **Work Done:** Captures the volume of material moved, crucial for tracking progress and productivity.
- **Hours Worked:** Indicates the total time spent on the activity, essential for labour and equipment utilisation analysis.
- **Delay:** Highlights any interruptions, with specific reasons provided (e.g., weather conditions), important for understanding project delays.
- **Start and Finish Date/Time:** Provides the timeline for the activity, helping to ensure that project schedules are adhered to.
- **Uptime:** Measures the effective working time, excluding any delays, which is important for evaluating efficiency.
- **Crew:** Identifies the team responsible for the activity, useful for accountability and performance tracking.
- **Work Zone:** Specifies the exact area of the site where the activity is performed, aiding in site management and coordination.
- **Location:** Offers a broader context of where the activity is taking place within the site, useful for logistical planning.

Currently, data collection for daily excavation productivity is specifically managed by spotters, who track vehicle entries and exits, while the responsibility for reporting this data typically falls to junior staff or graduate engineers. Typically, in LXRPs subcontractor contracts dictate the frequency and precision of data collection, self-perform costing produces more precise results. However, lump sum contracts may provide a reduced level of detail and have the potential to overestimate the number of crew members. Although there may be variations in the data requirements for different activities, the reporting frequency remains consistent. Monitoring task operational periods and equipment types presents obstacles. Spotters perform manual data entry during the reporting process, which is subsequently imported into template spreadsheets. The Alliance, for the purpose of reporting, and LXRP, whose key goal is to enhance productivity in current and future projects are the principal stakeholders in this data.

The daily excavation volumes are substantially impacted by the soil or rock type being excavated. Initial visual classification of material to be excavated as Rock or Other Than Rock (OTR) impacts the assumed building factor. In this case study the bulk factor was taken to be 1.6 and the material classified as rock. Difficulties arise when excavating denser rock, frequently necessitating the utilisation of excavators rather than bulldozers; this results in increased expenses and duration. Contractor trucks may not be properly equipped for haulage of large rocks due to concerns about damage to their trays.

The absence of a weighbridge presents unique challenges for accurately measuring and validating the weight of material removed. Typically, a weighbridge allows for precise tracking of loaded and unloaded weights, which directly indicates the amount of material transported. Without this, the project relies primarily on truck counts and estimated truck capacities to infer the volume of material removed from the site.

To address this, this trial uses computer vision and AI tools to verify truck counts and loading cycles, including tracking bucket counts to monitor material per load. This AI-generated data will then be used for manual calculations of earthwork removal on-site, incorporating key factors such as fill factor and bucket factor to adjust for material compaction and bucket loading efficiency. This approach allows us to achieve accurate volume estimations based on AI-captured counts, while using manual adjustments to refine calculations according to site-specific conditions.

4.4 Computer Vision Objectives

The objective of integrating computer vision technology into the Dublin Road LXRP, specifically for earthwork removal, is to optimise operations by enhancing the accuracy and efficiency of tracking and analysing a variety of metrics related to labour, equipment usage, and environmental conditions. Here are the detailed objectives:

1. **Real-time Monitoring and Data Accuracy**:
    - Implement computer vision to provide continuous, real-time monitoring of earthwork activities.
    - Capture accurate data on the volume of earth moved, the positioning and operation of heavy machinery, and the tracking of progress against the project plan.
2. **Labour and Equipment Utilisation**:
    - Monitor the number of workers within the camera's field of view (FOV) to optimise workforce allocation and ensure that the appropriate number of personnel is deployed for effective earthwork removal.

- Track the quantity and usage hours of specific types of equipment present in the FOV, such as excavators, rippers, dozers, and loaders, to assess the effectiveness and efficiency of equipment utilisation.

3. **Operational Efficiency and Resource Optimisation**:
    - Use insights from computer vision to identify bottlenecks and inefficiencies in the earthwork removal process.
    - Optimise the deployment and utilisation of resources, reducing idle times, managing maintenance schedules effectively, and preventing overuse of equipment to reduce operational costs.
4. **Comprehensive Metrics and Cumulative Analysis**:
    - Collect cumulative metrics such as the total number of shifts, total number of workers and equipment, and the total amount of time that equipment is operational.
    - Provide a comprehensive overview of earthwork removal activities over time, enabling improved resource management and planning methods.
5. **Measurement and Verification**:
    - Use units such as cubic meters or bank cubic meters to measure the material that has been removed.
    - Determine the total amount of spoil removed based on the load-out excavator bucket unloads to trucks and the number of dump trucks leaving the site, while considering the types and sizes of trucks.
    - Compare the computed totals with the Fleet Plant Hire Dockets provided by the dump site and verify through manual inspections of camera footage and evaluations of dockets.

Figure 29. Weighbridges (Weigh-more Solutions)

4.5 Time Series[2]

Time series metrics are used to monitor key parameters throughout the earthwork removal process, specifically bucket counts and trucks in and out. These metrics will be tracked continuously throughout the day, with a focus on days with the highest excavation activity. Additionally, equipment count, and labour count will be tracked every 5 minutes of the footage. These metrics provide real-time data that helps project managers respond quickly to any operational inefficiencies, such as delays in earth removal or unexpected machinery downtime.

Table 8. Time series parameters for earthwork removal

Metric	Description	Data Type	Frequency
Labour Count	Tracks the total number of people detected within the camera's field	Count	Every 5 minutes
Equipment Count	Monitors the entry and exit of trucks to gauge material transport volume.	Count	Every 5 minutes
Trucks In and Out	Each piece of equipment's active/working hours are tracked to monitor uptime within the camera's field of view.	Count	Continuous
Bucket Count	Tracks the number of bucket cycles to estimate material moved.	Count	Continuous

Cumulative Metrics

Cumulative metrics aggregate data over the project duration to provide insights into overall achievements and resource utilisation, including total bucket cycles and truck movements. These metrics are essential for evaluating progress against planned goals and budgets, allowing project managers to make data-driven decisions to ensure the project remains on track.

Table 9. Cumulative metrics

Metric	Description	Data Type
Trucks In and Out	Monitors the cumulative entry and exit of trucks to gauge total material transport volume.	Count
Bucket Counts	Tracks the cumulative number of bucket cycles to estimate material moved.	Count

4.6 Hardware

System Components

- **Sensing Element:** Installation of camera(s) around the site as detailed in Table 10 and Table 11.
- **Data Storage**: Onsite hard disk uploaded to cloud storage hosted by Sightdata.
- **Processing Power**: Cloud based Sightdata artificial intelligence algorithms.
- **Network Connectivity**: 4G/5G connectivity to enable real-time data transfer to the cloud.
- **Power Source**: A combination of SLA/Lithium batteries and solar panels.

[2] HIVE Research & Development (2024b)

Camera Specifications and Recording

A summary of specifications is detailed in Table 10 and comprehensive details on camera specifications and video data collection, is summarised in Appendix C. Key features include 130 dB WDR for balanced imaging in challenging lighting conditions, efficient H.265+ compression technology, IP67 water and dust resistance, and built-in deep learning capabilities for human and vehicle detection. The camera supports multiple video streams with configurable resolutions and frame rates (up to 30fps at 1280×720), includes advanced features like motion and intrusion detection, and offers comprehensive connectivity options, including ONVIF compatibility. Although the camera's max resolution is 3840 × 2160 at 30 fps, for this trial recordings were done at 1280 × 720 at 8 fps to match with Sightdata requirements

The reduction in camera resolution from 3840×2160 (4K) to 1280×720 (720p) represents a significant decrease in pixel density by approximately a factor of 3, which directly impacts the camera's DORI (Detection, Observation, Recognition, and Identification) capabilities. According to the camera's datasheet specifications for the 4mm lens at full 4K resolution, the camera can detect objects at 102m, observe at 40m, recognise at 20m, and identify at 10m. When the resolution is reduced to 720p, these distances are correspondingly reduced by roughly the same factor of 3, resulting in new approximate effective ranges: detection at 34m (down from 102m), observation at 13m (down from 40m), recognition at 7m (down from 20m), and identification at 3m (down from 10m). This reduction significantly impacts the recognition capabilities, particularly in large construction sites where longer detection ranges are beneficial. This substantial reduction in spatial resolution suggests that the current configuration may be suboptimal for comprehensive site surveillance, especially in scenarios requiring detailed observation or identification at greater distances. Websites, such as JVSG[3], can be used to visualise these changes. When planning camera positions, use the Detection, Observation, Recognition and Identification specifications from the datasheet to create coverage maps. For example, with the 4mm lens, ensure that areas requiring identification (like site entrances) are within 10m of the camera, while general detection can work up to 102m away. Having overlapping coverage from multiple cameras also provides redundancy in case of camera failure or obstruction.

[3] https://www.jvsg.com/calculators/cctv-lens-calculator/

Table 10. Turret Camera (HIKVISION)

Feature	Details
Image Quality and Resolution	8 MP resolution; 24/7 Colour Imaging with F1.0 lenses and high-performance sensors (0.0005 Lux)
Compression and Storage	H.265+ Compression Technology; Supports microSD/SDHC/SDXC/TF cards up to 256 GB
Wide Dynamic Range (WDR)	130 dB WDR for high-contrast lighting conditions
Audio Capabilities	Built-in Microphone for real-time audio security (-U model)
Smart Features	Deep Learning Algorithms for human and vehicle classification; Face Capture and Smart Event Detection
Durability and Environment Resistance	IP67 Rating for water and dust resistance; Operating temperatures from -30°C to 60°C; Humidity up to 95%
Network and Protocols	Multiple Protocol Support (TCP/IP, HTTP, HTTPS, FTP, DHCP, DNS, RTP, RTSP, and more); Supports up to 6 channels for simultaneous live view
Lens and Field of View	Fixed Focal Lenses (2.8 mm and 4 mm options); Adjustable angles (Pan: 0° to 360°, Tilt: 0° to 75°, Rotate: 0° to 360°)

Table 11. Camera Locations

	Delivered On	Installed On	Adjusted On	Chainage (Location)	Heading
Camera 1 (Tower A)	Wednesday 10 Jan 2024	Wednesday 17 Jan 2024	Monday 22 Jan 2024	Chainage: 27700 (Gate 15)	WEST
Camera 2 (Tower A)	Wednesday 10 Jan 2024	Wednesday 17 Jan 2024	Monday 22 Jan 2024	Chainage: 27700 (Gate 15)	EAST
Camera 3 (Tower B)	Wednesday 10 Jan 2024	Wednesday 17 Jan 2024	Monday 22 Jan 2024	Chainage: 27540 (Gate 13A)	WEST
Camera 4 (Tower B)	Wednesday 10 Jan 2024	Wednesday 17 Jan 2024	Monday 22 Jan 2024	Chainage: 27540 (Gate 13A)	EAST
Camera 5 (Tower C)	Wednesday 24 Jan 2024	Monday 19 Feb 2024	Monday 19 Feb 2024	Chainage: 27750 (North Wall)	WEST
Camera 6 (Tower C)	Wednesday 24 Jan 2024	Monday 19 Feb 2024	Monday 19 Feb 2024	Chainage: 27750 (North Wall)	EAST
Camera 7 (Tower D)	Wednesday 24 Jan 2024	Monday 19 Feb 2024	Monday 19 Feb 2024	Chainage: 27630 (North Wall)	WEST
Camera 8 (Tower D)	Wednesday 24 Jan 2024	Monday 19 Feb 2024	Monday 19 Feb 2024	Chainage: 27630 (North Wall)	EAST

Figure 30. Camera Location in Dublin Road Trial provided by LXRP

4.7 Verification & Validation Approach

The Verification & Validation (V&V) procedure for this project checks the accuracy and reliability of computer vision models developed to track productivity on construction sites. This approach ensures the integrity of the data collected for productivity insights and validates AI model accuracy. The goal is to improve real-time monitoring of construction site activities by systematically verifying and validating models and data outputs.

Verification Process

The verification process evaluates the system to ensure it meets the functional requirements and specifications for productivity monitoring. Key steps include:

1. **Manual Labelling and Data Extraction via CVAT**:
   - The project team uses the Computer Vision Annotation Tool (CVAT) for manual labelling, focusing on detecting persons, equipment, trucks + trailers leaving the site, and bucket counts. This labelled data serves as the baseline for validating AI accuracy in detecting and counting key activities on-site.
2. **Object Count Comparison**:
   - The team compares manually labelled data from CVAT (for persons, equipment, trucks + trailers leaving, and bucket counts) against AI-generated data to verify alignment. Truck + trailer movements are cross-referenced with Load Sheet data from the site team, with counts recorded and analysed in an Excel spreadsheet to identify any discrepancies.
3. **Bucket Count Verification**:
   - Bucket counts, representing the number of times excavators load spoil into trucks, are manually tracked using CVAT for selected days. This process involves detailed manual counting of each loading event, which is then

documented in Excel to ensure that AI-generated bucket counts accurately reflect actual site activities.

4. **Truck + Trailer Exit Validation**:
   - The verification process includes tracking trucks + trailers leaving the site by comparing CVAT manual labelling with both AI-based counts and Load Sheet records. This step, recorded in Excel, ensures accuracy in volume estimations based on truck and trailer movements.

Validation Process

The validation process tests the AI system in real-world conditions to confirm its functionality and reliability for construction productivity analysis. This involves comparing AI-generated data with manually collected records from construction sites.

1. **Field Trials and Real-World Validation**:
   - Validation is conducted through field trials (e.g., the Dublin Road Trial), where the AI system's outputs are compared to data manually collected on-site. The AI's ability to count trucks, monitor equipment activity, and track spoil removal is validated against traditional tracking methods, such as those performed by spotters and site engineers.
2. **Comparison of Automated and Manual Data**:
   - Discrepancies between AI-generated productivity metrics (e.g., truck + trailer movements, material removal rates) and manually collected data are analysed. Adjustments are made to the AI model as necessary to align with actual field data.
3. **Error Analysis and Mitigation**:
   - The validation process also addresses sources of error, such as environmental factors (e.g., lighting variations, equipment overlap) that may impact AI detection accuracy. By understanding and mitigating these factors, the system's performance becomes more reliable across varying real-world conditions.

Date and Time Periods for Assessment

The selection of time windows for data analytics and validation is critical to ensure that manual labelling efforts align with the most relevant periods of construction activity. This allows the project team to focus on high-activity periods where the AI system's outputs—such as object detection, equipment utilisation, and spoil removal analytics—can be effectively compared to manual data for verification and validation purposes. The following criteria were employed:

1. **Footage Availability and Accuracy**:

   To perform effective validation, it was essential to work with accurate and available footage. Issues with inaccurate time labels in earlier footage uploads were resolved by 23 July 2024, and Sightdata provided labelled video files through Amazon Kinesis. The footage was cross-checked to ensure it was recorded during periods with high levels of activity in the camera's FOV. Only dates with available and relevant footage were selected for validation.

2. **High Activity Periods for Excavation and Haulage**:

   The time windows were selected based on haulage records and observed excavation activity. Load sheets and operational logs were used to identify the days with significant haulage truck movements and spoil removal activities, ensuring that these time periods offered valuable data for manual labelling and comparison with AI analytics. Selected dates focused on periods of substantial operational activity, maximising the relevance of the verification process and providing key opportunities to validate AI outputs.

For the purpose of **bucket counts for earthwork volume calculation**, the following high-activity dates were chosen, with both manual and AI-generated totals included:

- **9 Feb**: Bucket Counts:
  Manual – 716, AI – 749
- **16 Feb**: Bucket Counts:
  Manual – 762, AI – 744
- **28 Feb**: Bucket Counts:
  Manual – 641, AI – 632
- **29 Feb**: Bucket Counts:
  Manual – 1079, AI – 1118
- **15 Mar**: Bucket Counts:
  Manual – 598, AI – 717
- **18 Mar**: Bucket Counts:
  Manual – 443, AI – 389.

For **truck + trailer counts for earthwork volume calculation**, the following dates were prioritised, with manual labelling compared against load sheet data:

- **9 Feb**: Bucket Counts:
  Manual – 152, Load Sheet – 146 (Refer to Appendix X)
- **29 Feb**: Bucket Counts:
  Manual – 195, Load Sheet – 204
- **18 Mar**: Bucket Counts:
  Manual – 88, Load Sheet – 89.

These dates, selected based on observed high levels of excavation and haulage activity, provide critical periods for validating the accuracy of AI outputs, comparing them against manually collected data, and ensuring reliable estimates of earthwork volumes for the project.

Camera and Zone Selection:

Camera 4 was selected for this project due to its strategic placement in the high-activity area of **Zone 4**. Positioned to capture the loadout excavator, it plays a crucial role in monitoring spoil removal, truck counting, and equipment utilisation. This camera provides essential footage for validating AI-based analytics by capturing the key activities that drive productivity metrics.

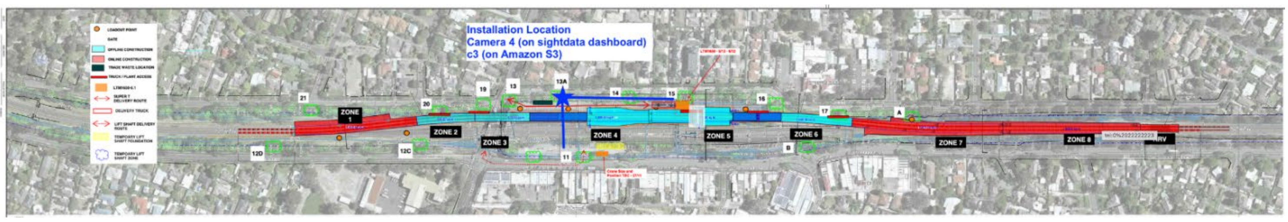


Figure 31. Camera 4 Location in Zone 4 at Dublin Road Trial, provided by LXRP

Metrics for Validation within Selected Date and Time Periods

During the selected time windows, the following metrics will be extracted and compared with AI-generated data to check accuracy:

- **Count of People**: Manual count of workers detected in the camera's field of view during selected periods, recorded in Excel.
- **Count of Equipment**: Verification of AI's detection of different types of equipment (e.g., excavators, trucks) using CVAT data, recorded in Excel.
- **Truck + Trailer Leaving**: Comparison of AI-generated counts of trucks + trailers leaving the site with manually recorded data from CVAT and Load Sheets.
- **Count of Buckets Unloaded to Trucks**: Manual tracking of each time an excavator loads spoil into trucks, cross-referenced with AI data, with all counts documented in Excel.

Dublin Road Trial Verification and Validation Tool

For this project, CVAT was used extensively for manual annotation of video footage to verify AI-generated data related to object counts, equipment usage, and bucket activities. This process involved systematic labelling to ensure precise validation of AI outputs.

Key Labelling Activities:

- Object Labelling: Every 300 frames (approximately every 5 minutes), each object visible on screen was labelled. Objects were only labelled if at least 50% was visible in the frame, following the AI model's criteria.
- Excavator Bucket Activity: Bucket activities were labelled, capturing the full scope of excavator usage throughout high-activity days.
- Truck Activity: Truck-leaving events were labelled, including detailed labels for scenarios like truck-trailer-leaving and no-tarp, to maintain precise records of all truck movements.
- Date and Timestamp Tagging: Timestamps were added at 5-minute intervals using bounding boxes, and adjustments were made incrementally to maintain consistency.

4.8 Computer Vision Metrics

A variety of metrics are used in the analysis to see how the AI-based computer vision models perform for various tasks/objectives. In this project, the primary objectives are to analyse the performance in:

1. counting buckets (dirt load counts) when excavators load dirt to loadout-trucks
2. counting people on the scene
3. detecting objects (equipment and plants of interest).

No single metric can measure the performance of AI models. Hence, we use a range of metrics to capture different aspects of the problem while performing the above tasks. Some metrics are suitable for specific tasks, and so are others.

Table 12 summarises the key metrics used in assessing the performance of the computer vision AI for object and person detection.

Table 12. Common metrics used to measure the performance of AI models in this project

Metrics	Description	Range (of values)	Comments
Accuracy	Measures how close the predicted values are to the actual values. It is often expressed as a percentage.	0 to 100 %	The higher the values (close to 100%), the better the model.
Total Count Error	Measures the sum of differences between predicted counts and ground truth counts across all instances. It measures the overall bias of the model in terms of total objects counted	-∞ to +∞	Close to 0 is better.
Mean absolute error (MAE)	Indicates the average difference between the absolute values of manual and AI-detected counts for specific video frames	0 to +∞	A lower MAE (close to zero) is ideal
Root Mean Square Error (RMSE)	Measures the average difference between actual and predicted values. RMSE is always positive and indicates the standard deviation of the residuals.	0 to +∞	An RMSE of close to zero indicates that the AI model makes fewer errors
Correlation Coefficient	Measures the strength and direction (sign) of a linear relationship between actual and predicted variables.	-1 to +1	+ve sign indicates better correlation -ve sign indicates less correlation 0 – no correlation
Overcounting Rate	Number of times the predicted values exceed the actual values for a particular period	0 to 1 or (0% to 100%)	Indicates a bias in the model. Close to 0 is better.
Undercounting Rate	Number of times the predicted values are lower than the actual values	0 to 1 or (0% to 100%)	Indicates a bias in the model. Close to 0 is better.
Cumulative Sum Difference	Difference between the sum of cumulative counts of actual values and predicted values	-∞ to +∞	+ve means overcounting -ve means undercounting Close to 0 is better.
Mean Count Difference	Measures the average counting bias for each object category. It helps to identify if certain object types are consistently over/under counted	-∞ to +∞	+ve means overcounting -ve means undercounting 0 means balanced predictions on average, but errors can still exist
R-squared	Measures how well the model captures count variations. It also shows if the model is better than simply guessing the average count. It helps to identify if the model is learning meaningful patterns.	-∞ to 1	1 – perfect prediction 0 – predicting the mean -ve - worse than mean >0.8 implies excellent performance 0.75 means the model explains 75% of the variability in the ground truth counts 0.0 means the model explains none of the variability -0.5 means the model's predictions are 50% worse than just using the mean

4.9 Earthwork Volume Metrics

We employ a variety of metrics specifically tailored to measure the accuracy and efficiency of earthwork volume estimation. The primary objectives in using these metrics are:

1. **Counting bucket cycles** to estimate the volume of material loaded by excavators.
2. **Tracking truck + trailer movements** to quantify the material transported off-site.
3. **Calculating loose and bank cubic metres (LCM and BCM)** to represent material volumes in loose and in-situ states, respectively.

Given the complexities of excavation, no single metric suffices for accurate volume measurement. Instead, a set of metrics is used to validate and compare AI-generated and manually recorded data. Below is an overview of each earthwork volume calculation metric.

Table 13. Earthwork-Specific Volume Metrics

Metrics	Description	Units	Comments
Bucket Counts	Total number of bucket cycles recorded for a given period, manually labelled or AI-generated	Count	Used to calculate LCM by multiplying with Heaped Bucket Capacity
Heaped Bucket Capacity	The calculated capacity of each bucket load based on bucket size and fill factor.	Specific to bucket size and fill factor	Accurate for estimating bucket load volume under actual site conditions, such as tough clay
Truck + Trailer Leaving Counts	Total count of trucks + trailers leaving the site during a selected period, based on data from Manual labelling on CVAT, Load Sheets, and AI detection	Count	Cross-referenced with manual Load Sheets, AI-generated data, and CVAT labelling for validation and accuracy in volume calculations
Loose Cubic Metres (LCM)	The volume of material moved in a loose state, calculated from bucket counts	Cubic meters	LCM = Total Bucket Counts × Heaped Bucket Capacity
Bank Cubic Metres (BCM)	Adjusted volume accounting for material expansion, representing in-situ volume	Cubic meters	BCM = LCM / Bulk Factor, typically using a bulk factor of 1.6

4.10 Earthwork Volume Analysis

Accurate measurement and monitoring of earthwork volumes are critical components of the level crossing removal productivity analysis. This section focuses on the application of computer vision and AI technologies to enhance the tracking and calculation of earthwork volumes for the Dublin Road Level Crossing Removal trial. The earthwork volume analysis used two primary methods: bucket counting and truck/trailer movement tracking. Both approaches apply computer vision algorithms to detect and quantify key activities related to earth removal and transportation. In the bucket counting method, AI models are trained to identify and count the number of times excavators load soil into trucks or trailers. By combining these counts with known bucket capacities and material expansion factors, the LCM of material excavated and subsequently calculate the BCM can be determined. Additional to this approach is the simpler but less granular truck/trailer movement tracking method, which utilises computer vision to monitor the exit of trucks and trailers from the construction site. By correlating these vehicle movements with their respective load capacities, an estimate for the total volume of material transported off-site can be performed. The earthwork volume analysis section presents a detailed evaluation of these two methods, including the underlying assumptions, calculation methodologies, and a comprehensive comparison of the AI-generated results against manually collected data from site teams and load sheets.

As discussed two primary measurements are used: **LCM** and **BCM** (Davidson, 2017).

- **LCM** refers to the volume of material in its loosened state, typically measured after it's excavated. LCM accounts for the material expansion that occurs when it's disturbed, making it ideal for estimating transportation requirements.
- **BCM** represents the in-situ or original volume of the material in its compacted state, before excavation. BCM is essential for calculating the actual volume removed, as it adjusts LCM by a bulk factor (e.g., 1.6), accounting for expansion.

Field measurements

These measurements were derived from the site-team

1. **Load Sheet Data (Truck + Trailer)**:
   - **Description**: Load sheets, manually recorded by on-site spotters, track essential details such as the time in and time out of trucks and trailers, along with the type of material loaded and the specific zone of removal. This documentation provides a precise log of daily earthwork operations and helps track each vehicle's entry and exit times, serving as a foundation for calculating total earthwork movement.
   - **Verification and Cross-Referencing**: Load sheet data can be cross-referenced with video footage to check accuracy and validate the manually recorded information. Differences between manual entries and footage timestamps can indicate potential discrepancies that need further investigation.

Table 14. Total Truck + Trailer Recorded by Spotters (Camera 4 Location)

Date	Total Loads
8 Feb 2024	65
9 Feb 2024	146
16 Feb 2024	145
28 Feb 2024	131
29 Feb 2024	204
15 Mar 2024	169
18 Mar 2024	89

Table 14 provides a record of the number of truck and trailer departures from a specific location where Camera 4 is positioned. This data was manually recorded by on-site spotters and captures daily earthwork activities by noting each time a truck or trailer leaves the site.

2. **Earthworks Cut Data (Earthworks Removal)**:
   - **Description**: Earthworks cut data captures the volume of material excavated from various zones, categorised by truck and trailer entries and exits. This dataset records which materials were removed from specific zones, using the entry and exit times as a way to correlate earthwork activities accurately.

- **In Practice on Site Volume Records**: By using truck and trailer timestamps for time in and time out, along with material and zone information, the site team calculates earthwork removal volumes on-site.
- **Use for Validation**: This data supports cross-referencing with other field measurements to ensure consistency in the recorded earthwork volumes. By aligning this data with manually collected information and automated methods, teams can verify the accuracy of the reported excavation progress.

Table 15. Earthworks Removal Volume (BCM) By Zone Recorded by site team (LXRP 2024)

Date	Earthworks Cut Data By Zone (BCM)		Total
	Zone 3	Zone 4	
9 Feb 2024		1139.6	1139.6
16 Feb 2024	803	803	1606
28 Feb 2024	1441		1441
29 Feb 2024	663.3	1547.7	2211
15 March 2024	929.5	929.5	1859
18 March 2024	489.5	489.5	979

Table 15 provides the daily volume of material excavated from Zone 3 and Zone 4, measured in BCM. Although Camera 4 monitors only Zone 4, data from both zones is recorded because material from Zone 3 is pushed into Zone 4 for final removal.

Bucket Counts

Key Assumptions

1. Fill Factor: A fill factor of 0.85 was used for the excavator bucket capacity, which corresponds to operations in tough clay conditions. This accounts for the partial filling of the bucket due to the material's tendency to not fully load the bucket (Appendix E).
2. Bulk Factor: A bulk factor of 1.6 was applied based on the material characteristics, which results in a volume increase of 60% when the material is excavated and becomes loose.
3. Heaped Bucket Capacity: The heaped bucket capacity was calculated using the nominal bucket size multiplied by the fill factor, providing an accurate estimate of the actual bucket load.
4. Zone Analysis Focus: The analysis focused primarily on Zone 4 because earthworks removal from Zone 4 included material from both Zone 3 and Zone 4. This approach was taken to ensure that the entire scope of removed material was captured in a consolidated analysis.

Methods

The methods for assessing the performance of the computer vision as well as the accuracy of site-based observations are as follows:

1. **Data Collection comprised three sources:**
   A. Manual Ground Truth Labelling (CVAT): The LXRP team and University of Melbourne team manually labelled bucket counts using the Computer Vision Annotation Tool (CVAT). This involved visually identifying and counting the cycles of the excavator buckets from video footage, providing a human-verified count.
   B. AI-Based Monitoring (Sightdata): Bucket counts were also captured using AI-based monitoring from Sightdata, which automatically analysed video footage to identify and count the excavator bucket cycles.
   C. Earthworks Cut Data: The recorded BCM data from the site team was extracted for Zones 3 and 4 to compare with the results calculated from bucket counts obtained through Manual Labelling and AI-based monitoring
2. **Calculation of Heaped Bucket Capacity:** The heaped capacity for each excavator was calculated using the formula:
   - Heaped Capacity = Bucket Size × Fill Factor

   For example, for the Komatsu PC490LC with a bucket size of 2.7 m^3 and a fill factor of 0.85:
   - Heaped Capacity = 2.7 × 0.85 = 2.295 m^3
3. **Calculation of Loose and Bank Cubic Meters (LCM and BCM):**
   - The total Loose Cubic Meters (LCM) for Zone 4 was determined using the formula:
     - LCM = Total Bucket Counts × Heaped Bucket Capacity
   - The Bank Cubic Meters (BCM) was then derived using the bulk factor:
     - BCM = LCM / Bulk Factor
4. **Comparison and Validation:**

   The BCM values obtained from bucket counts labelled manually via CVAT and using the AI-based monitoring (Sightdata) were compared against the recorded Earthworks Cut Data for Zones 3 and 4.

Results

Table 16. Comparison table between Manual labelling vs AI vs Earthworks Cut Data

Comparison between Manual Ground Truth Labelling, AI vs Earthworks Cut Data			
Date	**Manual Ground Truth (BCM)**	**AI (BCM)**	**Earthworks Cut Data (BCM)**
9 Feb 2024	1027	1074	1140
16 Feb 2024	1092	1067	1606
28 Feb 2024	919	906	1441
29 Feb 2024	1547	1603	2211
15 Mar 2024	857	1028	1859
18 Mar 2024	484	425	979

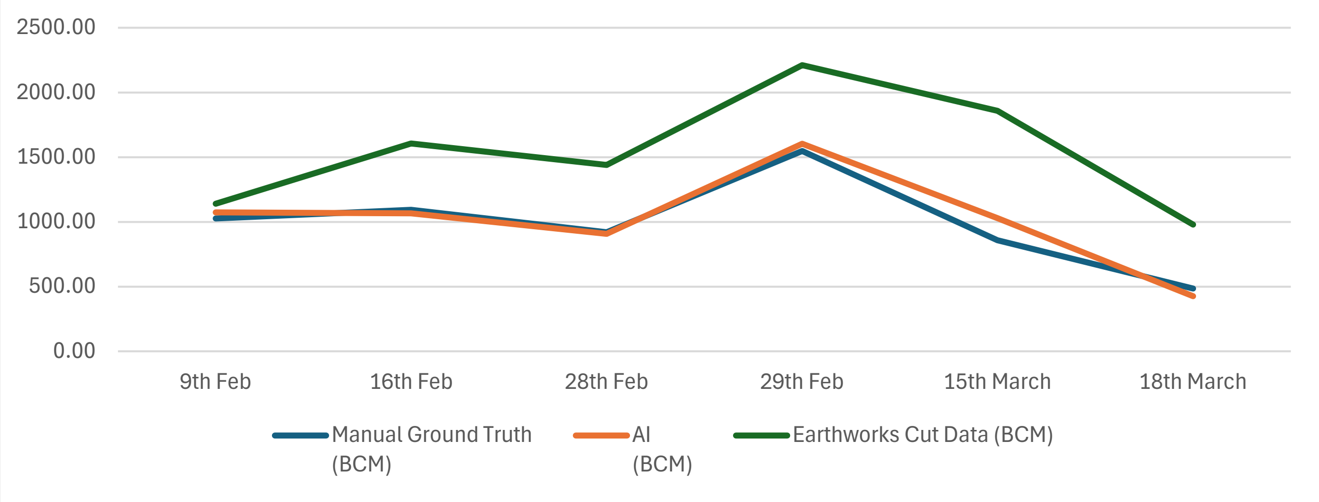


Figure 32. Comparison graph between Manual Ground Truth labelling, AI vs Earthworks Cut Data

As shown in Figure 32, the AI counted volumes aligned very well with the manual ground truths, however it was clear that the site-based investigations consistently overestimated the volume of material being removed from site. There are several possible reasons for this, however form observing the loadout excavator for several days it was evident that many trucks were underloaded. For example, often each truck and trailer were only loaded with four buckets which approximates to 9.2 LCM whereas most often they were loaded with five buckets equal to 11.5 LCM or rarely six buckets equalling 13.8 LCM. Based on site team reporting it appears that truck trailer combinations were all assumed to have 12.5 LCM which exceeded the average actual volume in each truck trailer combination. This is an important finding as it highlights the prevalence of underloading and the subsequent inefficiency and inaccuracy of existing methods.

Further to this a detailed analysis of counting the number of bucket-loads of dirt identified by an AI algorithm is compared to manual labelling as shown in Table 17.

Table 17. Summary of bucket count analysis

Date	Actual	Predictions (AI)	Accuracy (%)	Overcounting Rate (%)	Undercounting Rate (%)	MAE (%)
9 Feb 2024	716	749	96.98	3.02	0.00	3.02
28 Feb 2024	641	632	99.18	0.00	0.82	0.82
29 Feb 2024	1079	1118	96.51	3.49	0.00	3.49
15 Mar 2024	598	717	89.11	10.89	0.00	10.89
18 Mar 2024	443	389	95.06	0.00	4.94	4.94

For the five days (9 Feb, 28 Feb, 29 Feb, 15 Mar, and 18 Mar of 2024), the accuracy of the predictions by the AI algorithm ranges from 89% (15 Mar) to 99.18% (29 Feb). The maximum overcounting rate (10.89%) is observed on 15 Mar, and undercounting rate (4.94%) on 18 Mar. The maximum MAE is 10.89 (bucket counts), followed on 15 Mar.

The hourly bucket counts for actual, and AI counted for 18 Mar 2024 are summarised in Figure 33. It is clearly evident that while generally accurate, early morning counts were not captured due to sun glare on the camera lens (discussed later in the report).

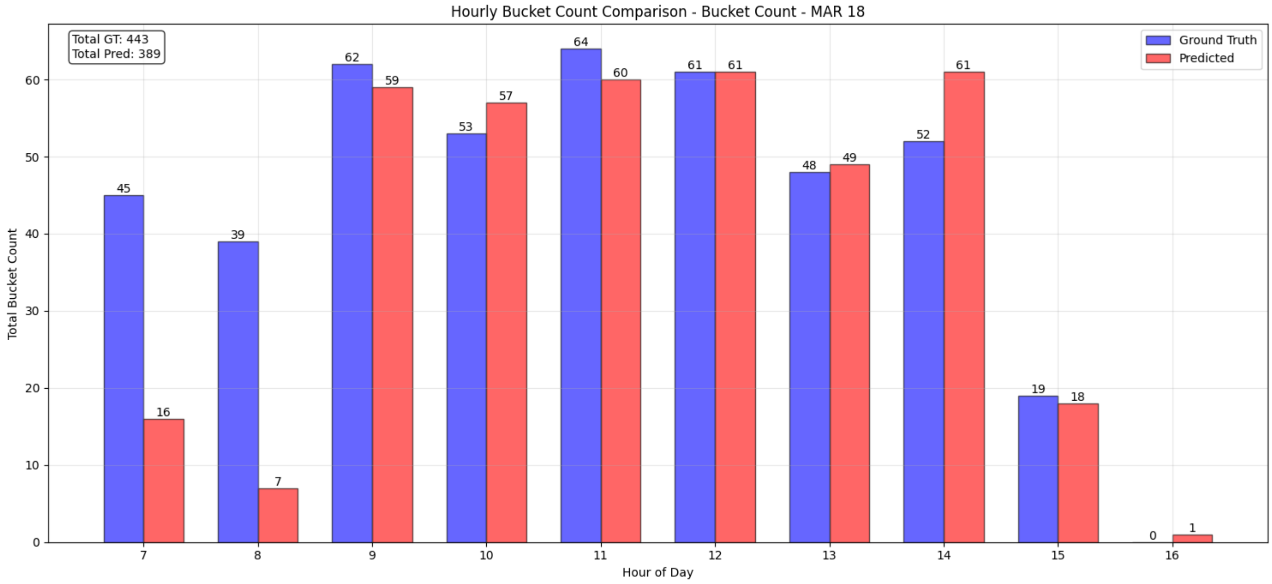


Figure 33. Comparison of hourly bucket counts on 18 Mar 2024

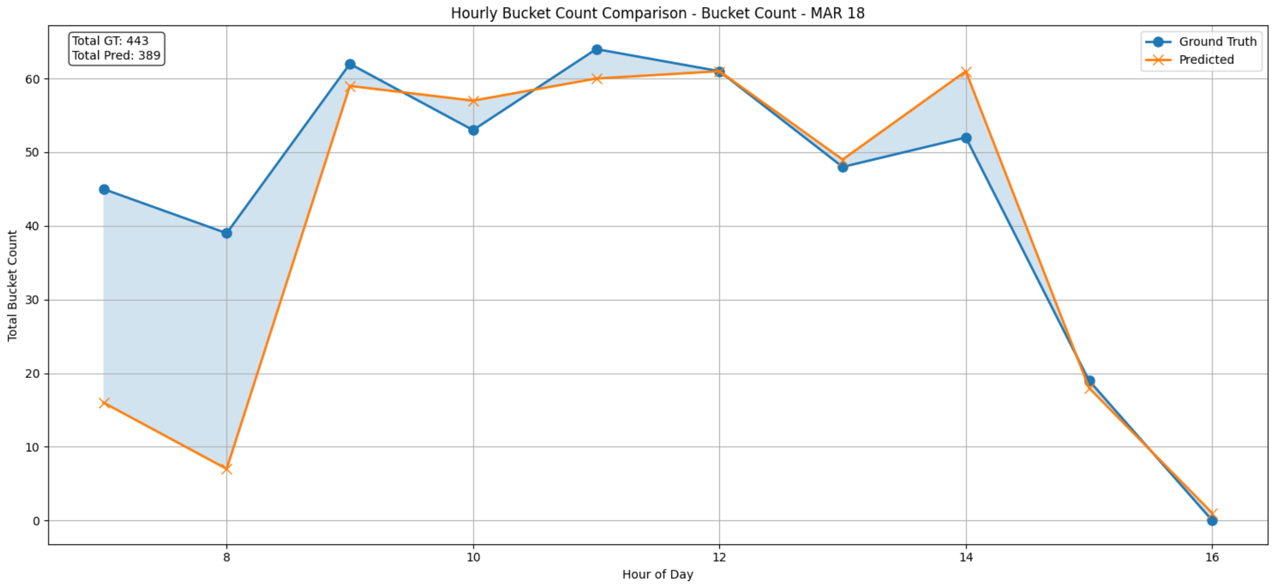


Figure 34. Comparison of hourly bucket counts, highlighting the difference between counts on 18 Mar 2024

The results for the remaining four days (Feb 09, Feb 28, Feb 29 and Mar 15) are presented in Appendix E.

Discussion

1. Manual Ground Truth vs AI

Table 18. Comparison Table between Manual Ground Truth vs AI

Date	Manual Ground Truth (BCM)	AI (BCM)	Difference (%)
9 Feb 2024	1027.01	1074.35	4.6
16 Feb 2024	1092.99	1067.18	-2.4
28 Feb 2024	919.43	906.53	-1.4
29 Feb 2024	1547.69	1603.63	3.6
15 Mar 2024	857.76	1028.45	19.9
18 Mar 2024	484.81	425.71	-12.2

- On most dates, the **Manual Ground Truth** and **AI-based counts** align closely, with differences of less than 10%, indicating good consistency (e.g., **9 Feb, 16 Feb, 28 Feb, and 29 Feb**).
- **15 Mar** shows a significant positive difference, where AI (1028.45 BCM) estimates were nearly 20% higher than manual counts (857.76 BCM). Conversely, **18 Mar** shows a negative difference of -12.2%, where manual counts were higher than AI estimates.

2. Manual Ground Truth and AI vs Earthworks Cut Data

Table 19. Comparison Table of Manual Ground Truth vs AI-Based Results Against Earthworks Cut Data

Date	Manual Ground Truth (BCM)	AI (BCM)	Earthworks Cut Data (BCM)	Manual vs Earthworks (%)	AI vs Earthworks (%)
9 Feb 2024	1027.01	1074.35	1139.6	-9.9	-5.7
16 Feb 2024	1092.99	1067.18	1606	-31.9	-33.6
28 Feb 2024	919.43	906.53	1441	-36.2	-37.1
29 Feb 2024	1547.69	1603.63	2211	-30.0	-27.5
15 Mar 2024	857.76	1028.45	1859	-53.9	-44.7
18 Mar 2024	484.81	425.71	979	-50.5	-56.5

- On **9 Feb**, both manual (1027.01 BCM) and AI (1074.35 BCM) estimates were close to the **Earthworks Cut Data** (1139.6 BCM), demonstrating reliable performance for both methods.
- On **16 Feb**, **28 Feb**, and **29 Feb**, significant discrepancies were observed, with manual and AI results showing more than 30% underestimations compared to the **Earthworks Cut Data**.
- **15 Mar** and **18 Mar** revealed the most substantial discrepancies, where both manual and AI estimates were significantly lower (over 40% lower) than the **Earthworks Cut Data**.

Findings

The considerable differences between Manual Ground Truth, AI-based counts, and the Earthworks Cut Data suggest potential underestimations in bucket count calculations. However, during the analysis, it was observed that some earthworks removal volumes recorded in both **Zone 3** and **Zone 4** were duplicated.

*When comparing Manual Ground Truth and AI-based BCM values using only **Zone 4** Earthworks Cut Data, the results show strong alignment, especially on key dates such as **9 Feb**, **29 Feb**, and **15 Mar**.*

Table 20. Comparison Table: Manual Ground Truth vs AI-Based Results and Zone 4 Earthworks Cut Data

Date	Manual Ground Truth (BCM)	AI (BCM)	Earthworks Cut Data (BCM)
9 Feb 2024	1027	1074	1139.6
16 Feb 2024	1092	1067	803
29 Feb 2024	1547	1603	1548
15 Mar 2024	857	1028	930
18 Mar 2024	484	425	489

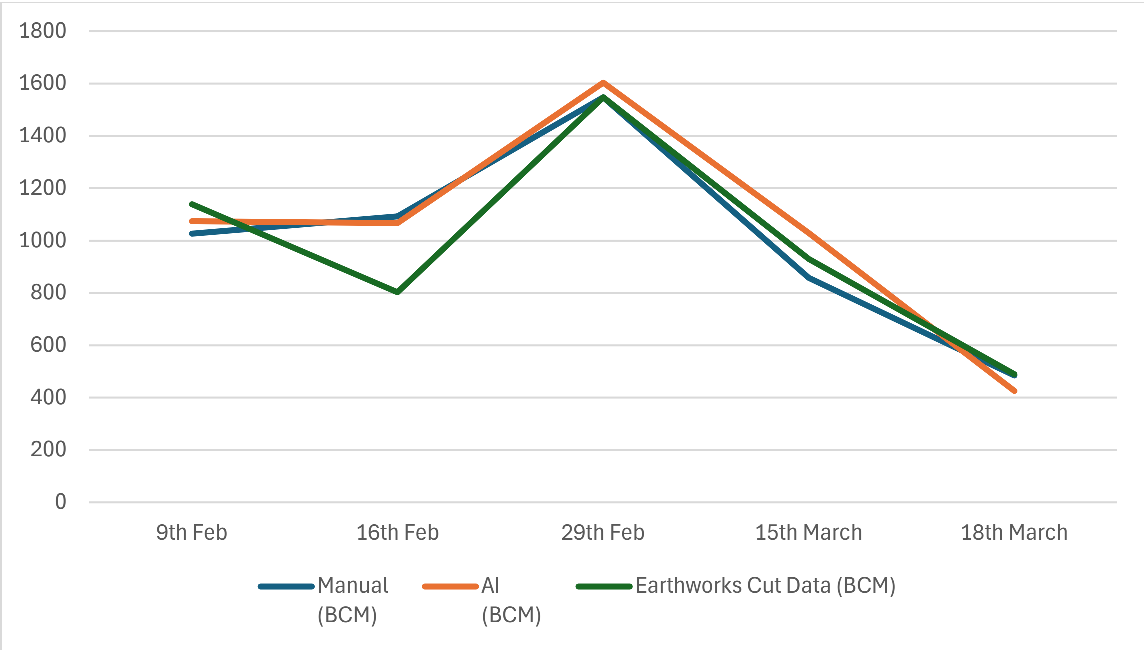


Figure 35. Comparison Graph: Manual Ground Truth vs AI-Based Results with Zone 4 Earthworks Cut Data

Truck and Trailer Count

A less granular approach to determining earthworks volume is by counting the trucks and trailers leaving using computer vision. This was trialled for several days with generally consistent results found between both computer vision and site-based recordings as detailed in Table 21 below. Here it can be seen that all methods of counting were within 5% of each other. Almost all trucks were truck trailer combinations, with a few single trucks, represented here as 0.5. Sightdata models were trained to disregards non-earthworks trucks as 'other trucks' and as such didn't count flatbed and other trucks unrelated to moving earth.

Table 21. Truck and Trailer Counts

Truck + Trailer Counts			
DATE	DAILY TOTAL - Manual Labelling	DAILY TOTAL - Load Sheet Data	AI
9th Feb	152	146	145.5
18th March	88	89	91.5

Figure 36 detailed results from the Sightdata computer vision for number of vehicles leaving the site in five-minute intervals. Here it can be seen that the vast majority of vehicles were truck and trailer combinations with one truck and eight other non-earthwork related vehicles.

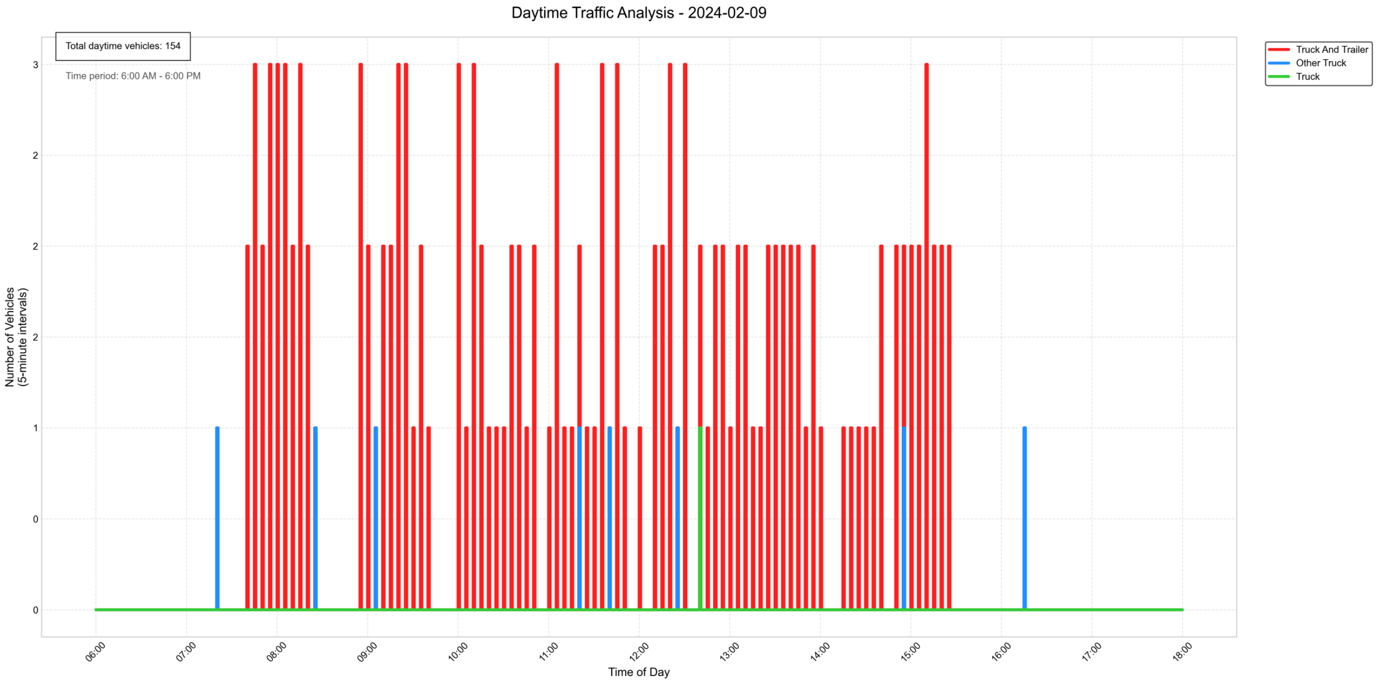


Figure 36. Five-minute results for truck and trailers leaving the site on 9 Feb

While truck counting using AI can be an effective method for estimating earthwork volumes its lack of granularity and reliance on an assumed volume for each truck means that it is not a particularly accurate measure for earthwork volumes. As was evident in the previous section assumptions relating to 'how full' each truck was differed by up to 25% from the actual volume placed in trucks by the loadout excavator. As such this report recommends the use of AI to track actual excavator loadout volumes rather than trucks leaving the site for the most accurate estimations of earthwork volumes.

4.11 People Count Analysis

The study evaluates the performance of AI-based people detection algorithms (developed by Sightdata) against manually annotated video frames using CVAT. The analysis spans eight days across February and March 2024 (8 Feb 8, 9 Feb, 15 Feb, 16 Feb, 28 Feb, 29 Feb, 15 Mar, and 18 Mar), comparing the accuracy of automated counting versus human-annotated ground truth data. The comparison utilises several key metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), correlation coefficients, and both overcounting and undercounting rates, to comprehensively assess the AI system's people detection capabilities under various construction site conditions.

Table 22 summarises the eight-day comparison results.

Table 22. Summary of performance comparison of AI predictions of people counts against actual counts

Date	Mean Absolute Error	Root Mean Square Error	Correlation	Overcounting Rate (%)	Undercounting Rate (%)	Cumulative Difference
8 Feb 2024	0.20	0.80	0.44	2.12	10.86	-109
9 Feb 2024	0.12	0.55	0.51	3.38	4.36	-14
15 Feb 2024	0.35	0.97	0.22	7.06	12.29	-85
16 Feb 2024	0.16	0.77	0.65	1.13	8.17	-95
28 Feb 2024	0.21	0.66	0.01	4.70	8.55	-58
29 Feb 2024	0.12	0.40	0.82	0.28	10.28	-84
15 Mar 2024	0.11	0.45	0.80	2.12	6.06	-45
18 Mar 2024	0.18	0.62	0.31	1.97	8.59	-73

Table 22 shows that the MAE is between 0.11 and 0.21, indicating that the AI model is reasonably accurate at predicting people's counts with a propensity to undercount (i.e. not detect people) on approximately 10% of frames assessed. The overcounting and undercounting rates (greater than zero) indicate that the model makes errors at certain times (false positives or false negatives), which results in cumulative differences between actual (ground truth) values and predicted values. Figure 37 shows the actual people count and AI-predicted counts for 18 Mar 2024.

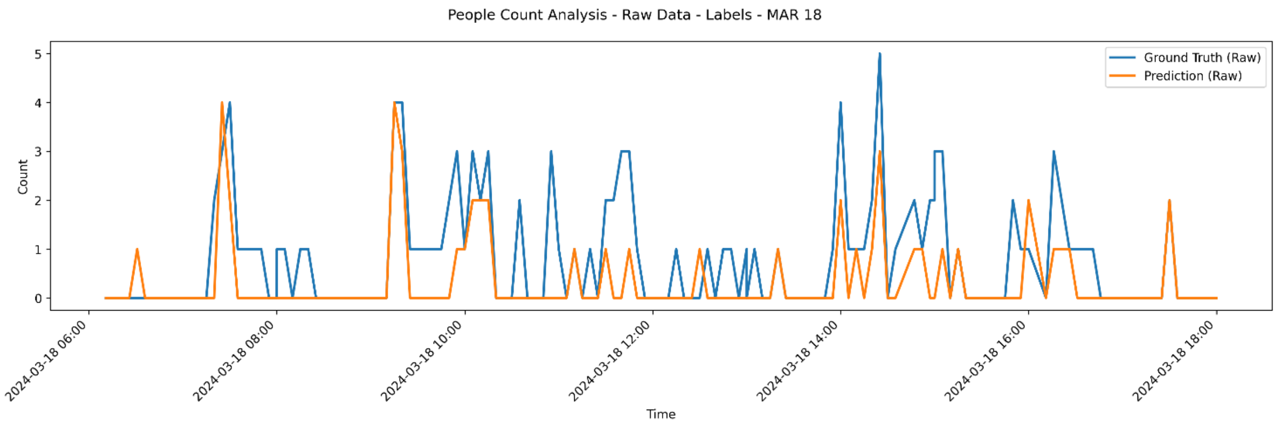


Figure 37. Number of people annotated vs number of people predicted by AI for 18 Mar 2024

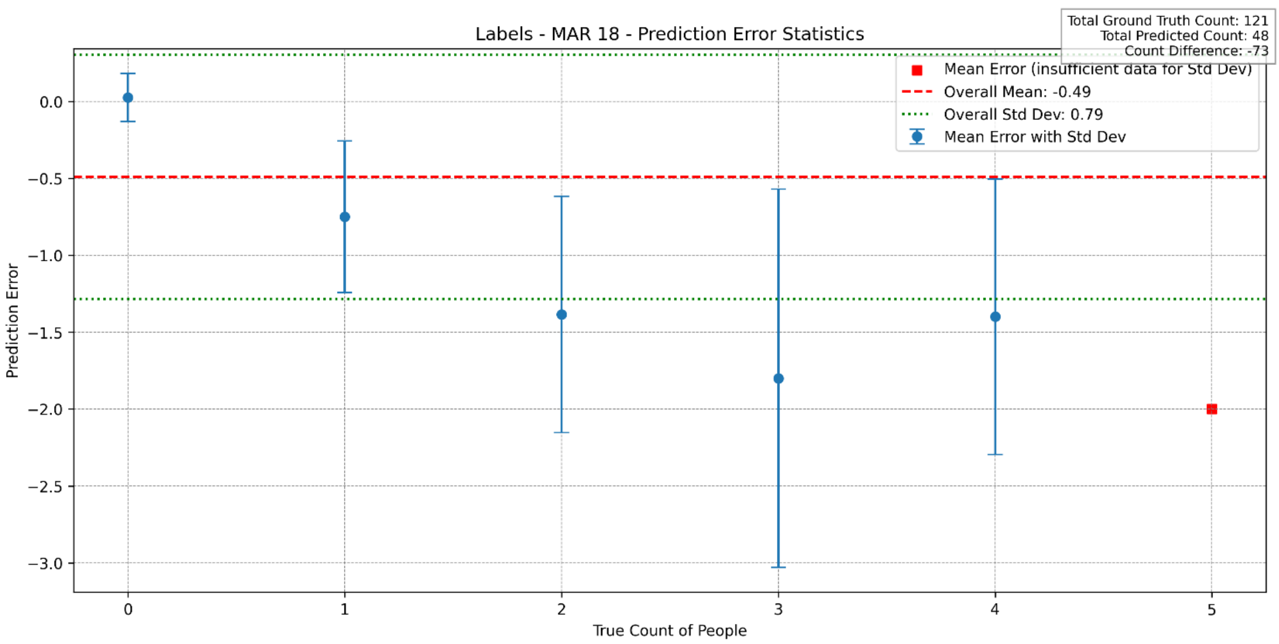


Figure 38. Prediction error statistics for 18 Mar 2024

Figure 38 shows the prediction error statistics regarding the number of people. In this instance, the overall mean error is -0.49, which is good. The negative sign indicates that the model undercounts and the overall standard deviation is 0.79 people. The figure also provides a detailed analysis of where it makes errors regarding the number of people. When no people are in the scene (i.e., the actual counts of people equal zero), the error is close to zero. Likewise, the error is less than -0.75 people when actual counts equal 1. When the actual number of people equals two, it makes an error of <-1.5 people; when there are three people, the model makes an error of -1.75; in the case of four people, it counts two fewer people than the actual counts.

Similar comparison graphs for other days (8 Feb, 9 Feb, 15 Feb, 16 Feb, 28 Feb, 29 Feb, 15 Mar) are listed in Appendix F.

4.12 Object Detection Analysis

This section compares the results of manually annotated objects (equipment and plant) against the AI-predicted results. There are eight object categories: bobcat, forklift, car, excavator, loadout-truck, person, telehandler and truck. However, due to inconsistencies in labelling bobcats and forklifts manually and difficulty in recognising them on cameras because of their small sizes, they have been merged as a single object (i.e., bobcat-forklift) in the following analysis. Although people counting analysis was presented in the previous section as a separate analysis, here, the 'person' object is included as part of object detection analysis for completeness. Sightdata runs a separate AI algorithm for detecting people; hence, a separate analysis was provided.

In this section, we provide the results for 18 Mar 2024. However, the results for the remaining seven days are provided in Appendix F. This section is divided into two subsections for clarity:

- Analysis for each day
- Analysis across days.

Analysis for each day

The analysis for each day mainly focuses on comparing the performance of AI model(s) against the ground truth for that day. Table 23 shows the AI model's performance for 18 Mar 2024, for seven object categories.

Table 23. Comparison results of AI predictions against manual annotations for 18 Mar 2024

Object	Ground Truth	Predicted	Total Count Error	Mean Count Difference	RMSE	Correlation	R squared	Overcounting Rate (%)	Undercounting Rate (%)
Bobcat-forklift	**25**	**18**	-7.00	-0.05	0.22	0.83	0.66	0.00	4.70
Car	**2**	**39**	37.00	0.25	0.50	0.32	-17.75	24.83	0.00
Excavator	**82**	**126**	44.00	0.30	0.66	0.10	-0.74	36.24	6.71
Loadout-truck	**0**	**31**	31.00	0.21	0.48	0.00	0.00	19.46	0.00
Person	**124**	**48**	-73.00	-0.49	0.93	0.71	0.32	2.68	37.58
Telehandler	**0**	**0**	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Truck	**65**	**18**	-47.00	-0.32	0.57	0.48	-0.15	0.00	30.87

The model showed varying levels of accuracy across the seven object categories, with some notable over- and under-counting issues. Excavators had the highest overcounting rate

(36.24%), with 126 predicted instances compared to 82 ground truth instances. Cars were also significantly overcounted (24.83%). For person detection, there was a substantial undercounting issue (37.58%), with only 48 predictions compared to 124 ground truth instances. The strongest correlation with ground truth was observed for bobcat-forklifts (0.83) and persons (0.71), suggesting more reliable detection patterns for these categories. Notably, telehandlers had zero detections and zero ground truth instances, indicating they were not present in the dataset for this day.

Figure 39 shows the cumulative counts of objects detected from 06:00 to 18:00 on March 18, 2024. It compares ground truth (GT, solid lines) against model predictions (Pred, dashed lines) for seven object categories. The graph effectively visualises both the temporal patterns of activity and the accuracy of the model's predictions compared to ground truth across different object types throughout the workday.

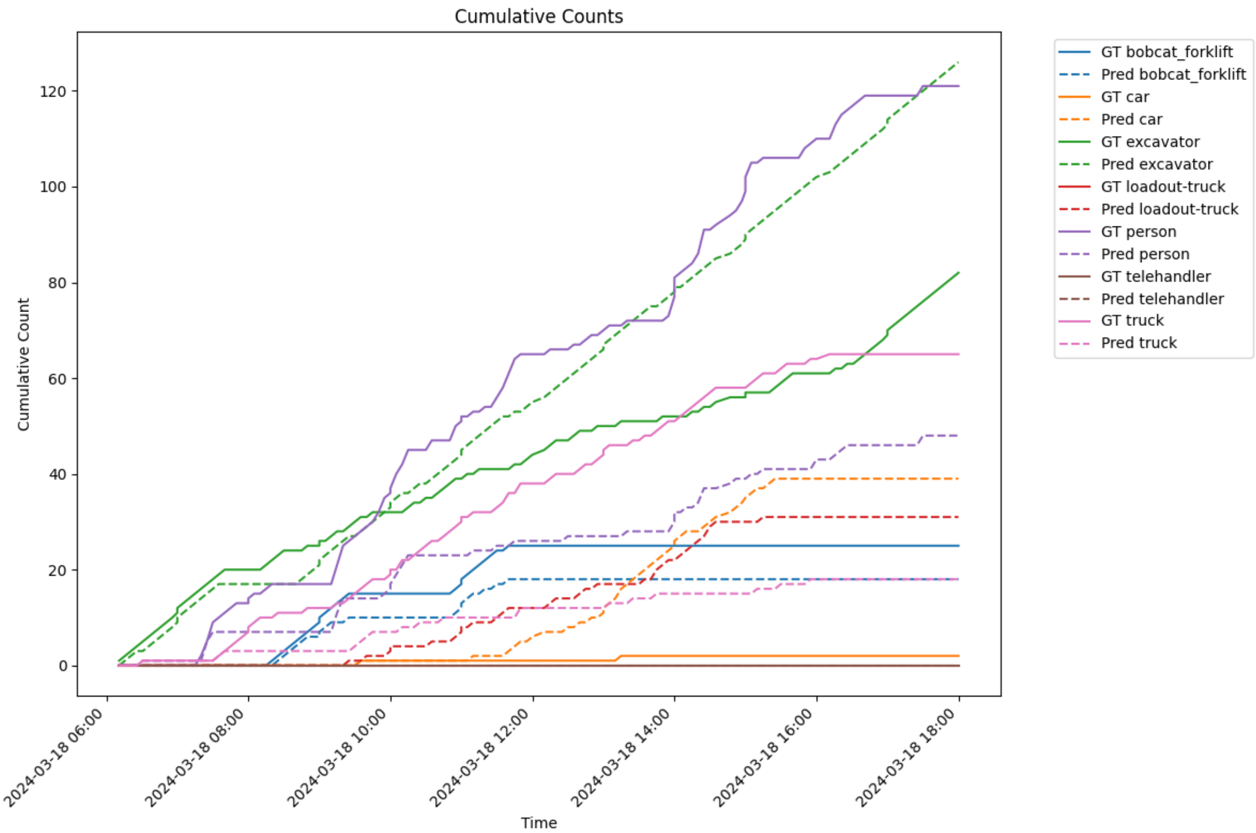


Figure 39. Cumulative counts of different objects detected throughout 18 Mar 2024, from 6:00 am to 6:00 pm

Throughout 18 Mar 2024, the cumulative detection data reveals distinct patterns in construction site activity and model performance. The site was most active with persons and excavators, accumulating around 120 counts by day's end, with peak activity occurring between 10:00 am and 2:00 pm. While the AI model generally tracked the actual activity patterns, there were notable discrepancies in its predictions. The site maintained moderate activity levels for trucks and bobcat-forklifts (around 60–65 total counts), while cars and loadout trucks showed lower presence throughout the day. Telehandlers were notably absent or had minimal activity. What's particularly interesting is the concentrated surge in activity during mid-day hours, suggesting this was the peak operational period for the construction site. Despite some counting discrepancies, the model's ability to follow these trends indicates it can effectively capture site activity's general rhythm and patterns, even if absolute count accuracy varies by object type.

Figure 40 shows the AI model's performance for 18 Mar 2024, in terms of hourly comparison. The four graphs collectively reveal essential patterns about the AI model's performance in monitoring construction site activity on 18 Mar 2024. The model demonstrates variable accuracy that appears to be strongly correlated with site activity levels – performing better during quieter periods and struggling during peak hours (10:00 am – 2:00 pm). A consistent trend across all visualisations is the challenge with person detection, showing systematic undercounting, while vehicles (particularly cars and excavators) tend to be overcounted. The hourly error patterns suggest that the model's accuracy deteriorates when the site becomes busier, possibly due to increased object overlap, occlusion, or complex interactions between different object types. The accuracy graph's volatility (between 0% and 100%) indicates that the model's reliability varies significantly throughout the day and across object categories. When examining total object counts, while the model captures general activity patterns, it tends to overestimate during busy periods, suggesting that high-density scenarios present the most significant challenge for accurate detection. These insights point to potential areas for model improvement, particularly in handling high-activity periods and maintaining consistent performance across all object categories.

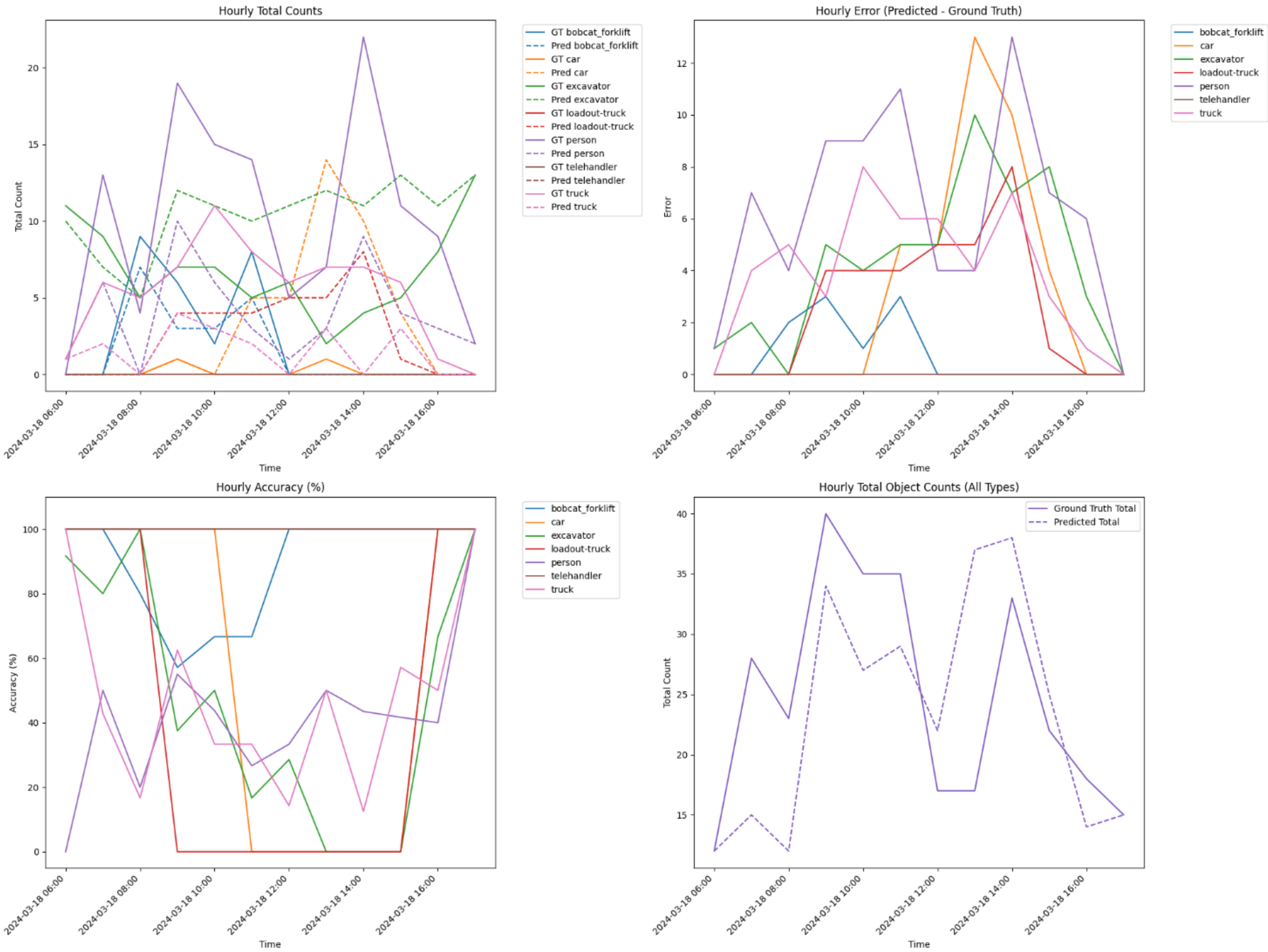


Figure 40. Hourly comparison of AI model's performance for 18 Mar 2024

Hourly Total Counts: The model's performance varied throughout the day, with notable discrepancies in counting different object types. Person detection showed the highest variability, with a significant peak around 2:00 pm. The model tended to undercount persons during peak hours but performed more consistently with excavators and trucks. There were periods where the model's predictions diverged significantly from ground truth, particularly during high-activity periods.

Hourly Error (Predicted – Ground Truth): The error analysis reveals systematic biases in the model's predictions. Cars and excavators showed positive errors (overcounting), reaching up to 12–13 instances per hour, while person detection often had negative errors (undercounting). The magnitude of errors increased during busier periods, suggesting the model struggles more with accuracy during high-activity times. The most significant errors occurred during mid-day hours, particularly between 12:00–3:00 pm.

Hourly Accuracy: The accuracy plot shows considerable volatility across different object categories. While some objects, like bobcat-forklifts and trucks, achieved 100% accuracy during certain hours, accuracy dropped significantly during others, sometimes falling to 0%. Person detection maintained moderate accuracy levels but showed consistent fluctuations. The model's performance was least stable during peak activity hours, with accuracy varying dramatically across all categories.

Hourly Total Object Counts (All Types): Looking at total counts across all object types, the model generally tracked the overall pattern of site activity but with notable discrepancies. The most significant gaps between predicted and ground truth totals occurred during peak activity hours (around 10:00 am – 2:00 pm). While the model captured the general trends of increasing and decreasing activity, it tended to overestimate total counts during busy periods, suggesting challenges in accurately distinguishing between objects during high-activity scenarios.

Analysis across days

In this section, we do additional analysis with advanced metrics to measure the AI model's performance. The study is conducted for all eight days of data collection for seven objects. Table 24 describes these metrics.

Table 24. Advanced metrics used to measure the performance of AI models in this project

Metrics	Description	Range of values	Comments
Exact Accuracy	Measures how often the system predicts exactly the correct number of objects	0 to 1 (0% to 100%)	It should be as high as possible (close to 1).
Within-one Accuracy	Measures how often the system's prediction is within ±1 of the actual count	0 to 1 (0% to 100%)	It should be higher than exact accuracy.
Small Count MAE	Average absolute error when counting 0-2 objects	0 to ∞ (typically 0–2)	It should be close to 0. Values above 0.5 indicate poor performance in detecting small numbers of objects
Medium Count MAE	Average absolute error when counting 3-5 objects	0 to ∞ (typically 0–3)	It should be close to 0. Values above 1.0 suggest issues with moderate object density
Large Count MAE	Average absolute error when counting >5 objects	0 to ∞ (typically 0–5)	It should be proportional to the count. Higher values more acceptable than for small/medium counts
False Positive Rate	The proportion of cases where the system detects objects when none are present	0 to 1 (0% to 100%)	Ideally should be close to 0.
False Negative Rate	The proportion of cases where the system misses objects that are present	0 to 1 (0% to 100%)	Should be close to 0.
Overcounting Frequency	The proportion of times the system predicts more objects than actually present	0 to 1 (0% to 100%)	Ideally, it should be close to 0.

Undercounting Frequency	The proportion of times the system predicts fewer objects than actually present	0 to 1 (0% to 100%)	Ideally, it should be close to 0.

Exact Accuracy

Figure 41 (heatmap) visualises the exact count accuracy of the AI model across different dates and object categories from February to March 2024, revealing exciting patterns in detection performance. Telehandlers show perfect accuracy (1.00) across all dates, possibly due to their consistent absence rather than successful detection. Cars demonstrate strong performance with consistently high accuracy (mostly above 0.90), while bobcat-forklifts show significant improvement over time, reaching excellent accuracy (0.88–0.99) in later dates despite early struggles (0.13-0.44). Excavators display a noticeable improvement trend, starting with lower accuracy (around 0.30) but improving to moderate levels (0.57–0.87) in later periods. Person detection remains challenging, with moderate accuracy (0.35–0.81) and inconsistent performance across dates. Loadout trucks and regular trucks show variable performance, with accuracy fluctuating considerably (trucks ranging from 0.18 to 0.95, loadout trucks from 0.42 to 0.92). **Overall, the model's performance generally improved towards the later dates (late February and March), suggesting possible refinements in the detection system over time or better adaptation to site conditions.** ***AI model was re-trained after 16 Feb 2024, which Sightdata confirmed***.

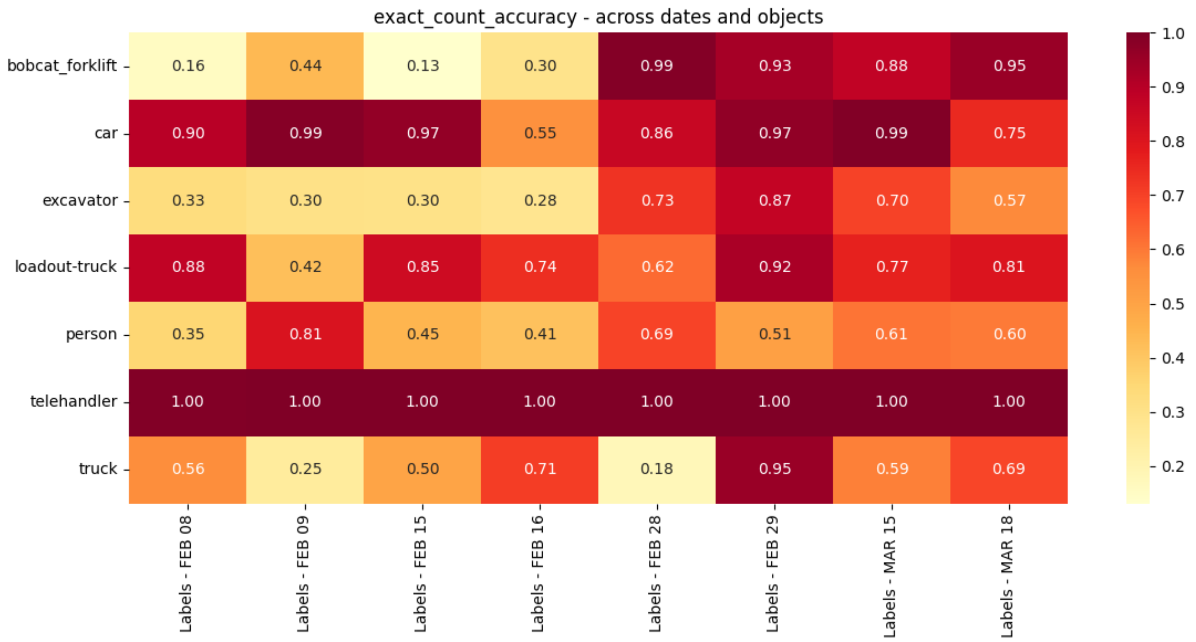


Figure 41. Exact accuracy comparison for 8 days

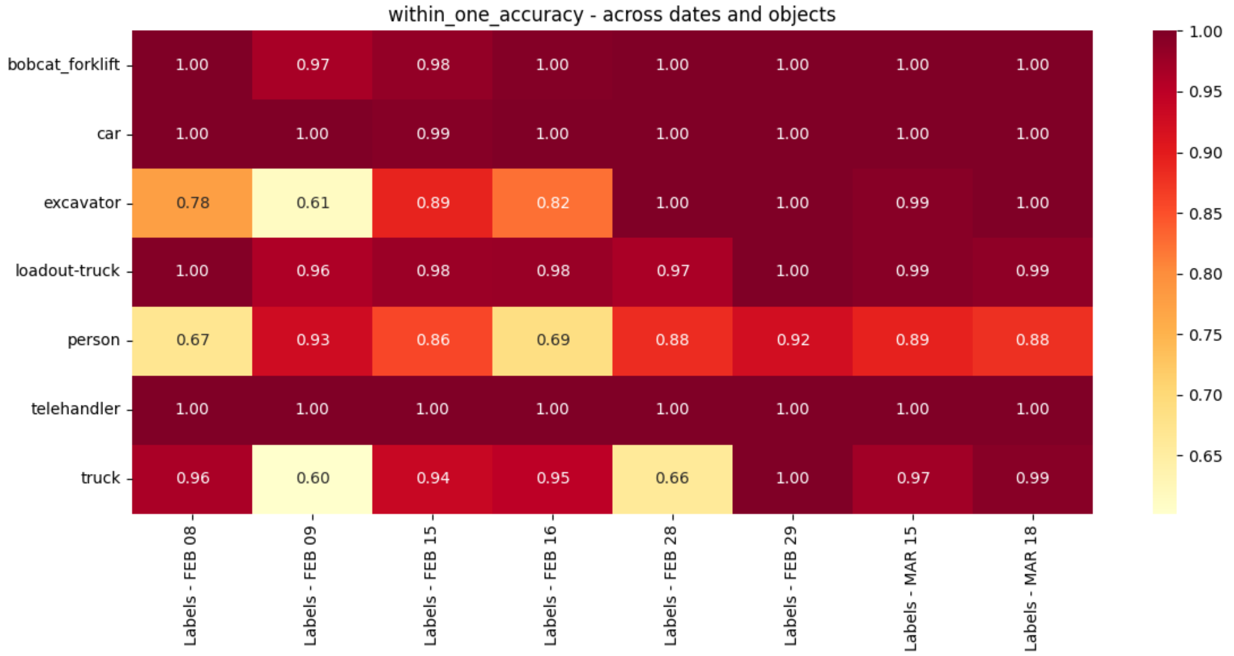


Figure 42. Within-one-accuracy metric comparison for 8 days

Figure 42 shows the '**within one accuracy**' metric across different dates and object categories, indicating when the model's count was within ±1 of the ground truth, revealing generally higher accuracy than exact counts. Almost all object categories demonstrate excellent performance, with accuracy frequently above 0.90. Telehandlers, cars, and bobcat-forklifts consistently achieve near-perfect accuracy (0.97–1.00) across all dates. Excavators show notable improvement over time, starting at moderate levels (0.61–0.78) in early February but reaching perfect or near-perfect accuracy (0.99–1.00) in later dates. Person detection, while still the most challenging category, performs significantly better under this metric (mostly above 0.85) compared to exact count accuracy, though with some fluctuations (lowest at 0.67). Loadout trucks maintain very high accuracy (0.96–1.00) throughout the period, and regular trucks show good performance despite some dips (notably 0.60 on 9 Feb and 0.66 on 28 Feb). **Overall, this metric suggests that while the model may not always predict the exact count, it consistently gets very close to the actual count for most object categories, indicating reliable performance for practical applications**.

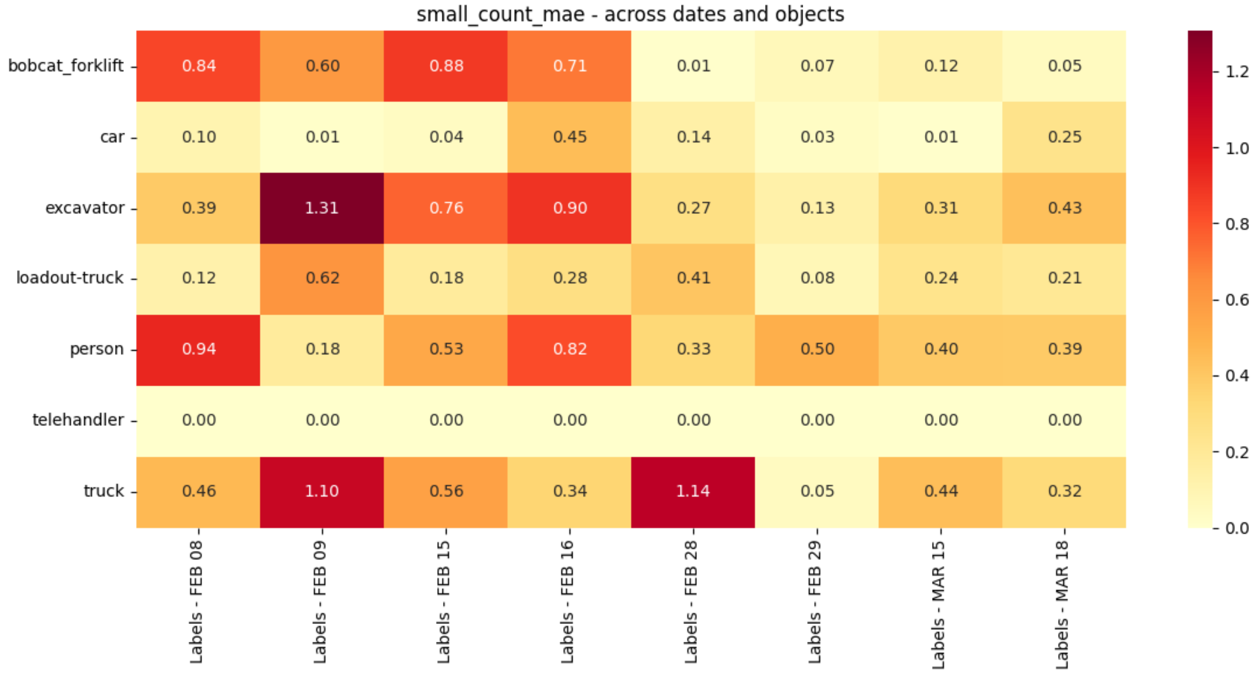


Figure 43. Small count MAE metric to compare AI model's performance across 8 days

Figure 43 shows the **Small Count MAE** across dates and object categories, where lower values (lighter colours) indicate better performance when objects were less than two. The model shows error levels across object types and dates, with some notable patterns. Telehandlers consistently show zero error (0.00) across all dates, though this likely reflects their absence rather than perfect detection. Cars generally maintain low error rates (0.01–0.25), indicating reliable detection accuracy. Excavators show more substantial errors, particularly on 9 Feb (1.31) and 16 Feb (0.90), suggesting challenges in accurate counting during these periods. Trucks also display higher error rates on specific dates (peaking at 1.14 on 28 Feb), indicating periodic difficulties in accurate detection. Person detection shows improvement over time, with early high errors (0.94 on 8 Feb) decreasing to more moderate levels (around 0.40) in later dates. The bobcat-forklifts show variable performance, with higher errors in earlier dates (0.60–0.88) but improving significantly in later periods (0.01–0.12). Overall, the model's error rates generally decreased towards later dates for most categories, suggesting improved performance over time, though some object types continue to present challenges for accurate counting.

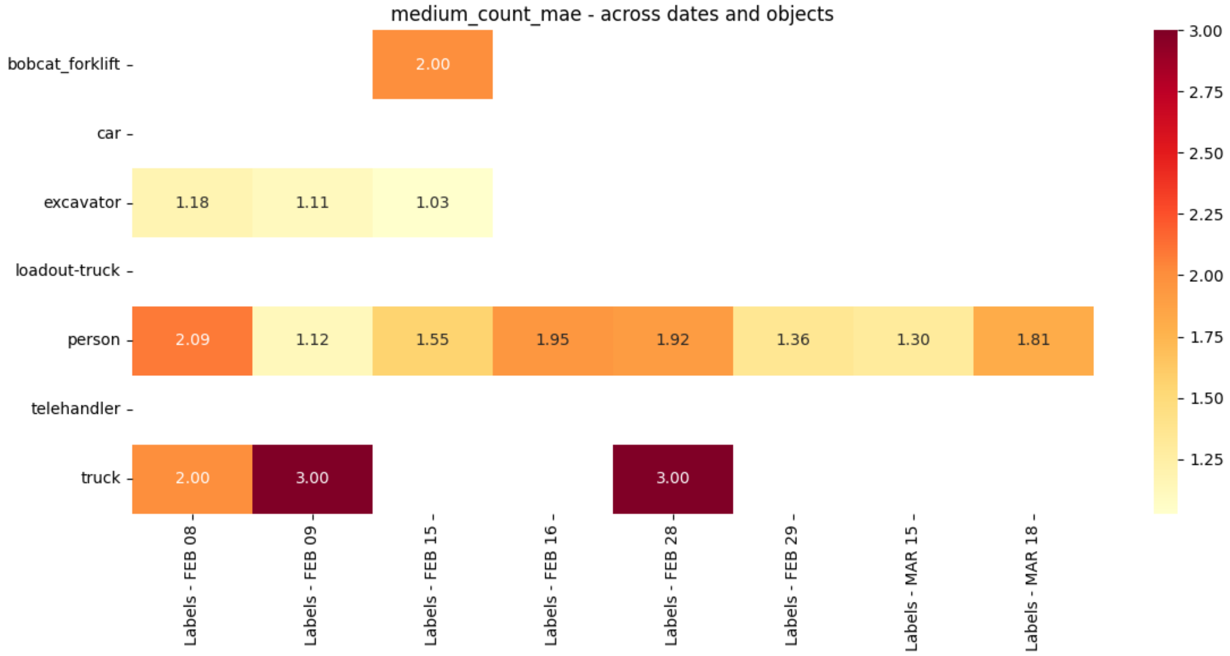


Figure 44. Medium count MAE metric to compare the AI model's performance across 8 days

Figure 44 shows the Medium Count MAE across dates and objects, revealing patterns in the model's performance with medium-sized counts (2–5 objects for each category). Person detection shows consistent presence across all dates but with varying error levels, starting high at 2.09 (8 Feb) and showing some improvement in later dates (dropping to 1.30–1.81), though errors remain substantial. Trucks show exceptionally high error rates (3.00) on specific dates (9 Feb and 28 Feb), indicating significant counting challenges during these periods. Excavators demonstrate relatively stable and lower error rates (1.03–1.18) across their observed dates, suggesting more consistent performance for this category. Bobcat-forklifts appear only once with a moderate error rate (2.00). At the same time, many categories show blank periods, indicating either the absence of medium counts or insufficient data for these object types during those times. The lack of data for telehandlers and loadout-trucks suggests these objects rarely appeared in medium-count scenarios. Overall, the model seems to struggle more with medium counts than small counts, with person detection being the most consistently challenging category requiring improvement.

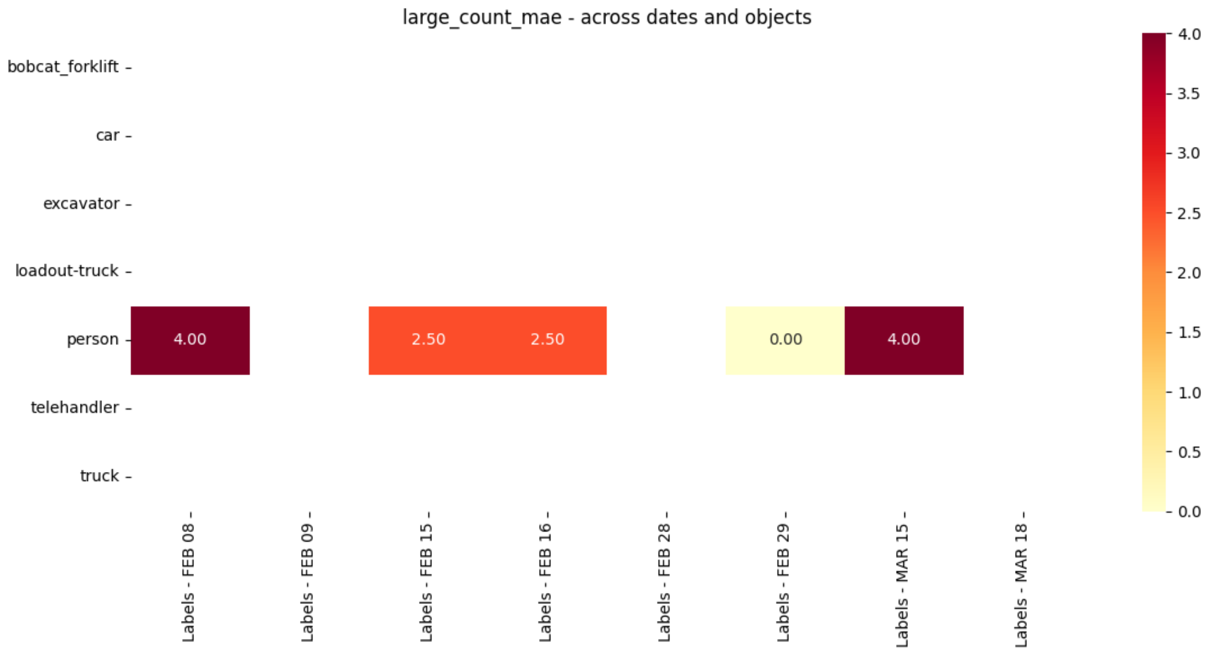


Figure 45. Large count MAE metric to compare the AI model's performance across 8 days

Figure 45 shows the **Large Count MAE** across dates and object categories when the number of object counts was in the range of 0–5 objects for each category. It reveals that only person detection had instances of large counts across the observed period, with significant error variations. The model shows considerable challenges in accurately counting large groups of people, with the highest MAE of 4.00 occurring in early February (8 Feb) and March (18 Mar). There was some improvement during mid-February (15 Feb and 16 Feb), where the error decreased to 2.50, and notably, one period (29 Feb) showed perfect accuracy with an MAE of 0.00. The complete absence of data for other object categories (bobcat-forklift, car, excavator, loadout-truck, telehandler, and truck) suggests that these objects rarely or never appeared in large numbers during the observation period. **This pattern indicates that managing large crowds of people remains the primary challenge for the model when dealing with high-count scenarios**. At the same time, other object types typically appear in smaller quantities that are handled by the small and medium count metrics.

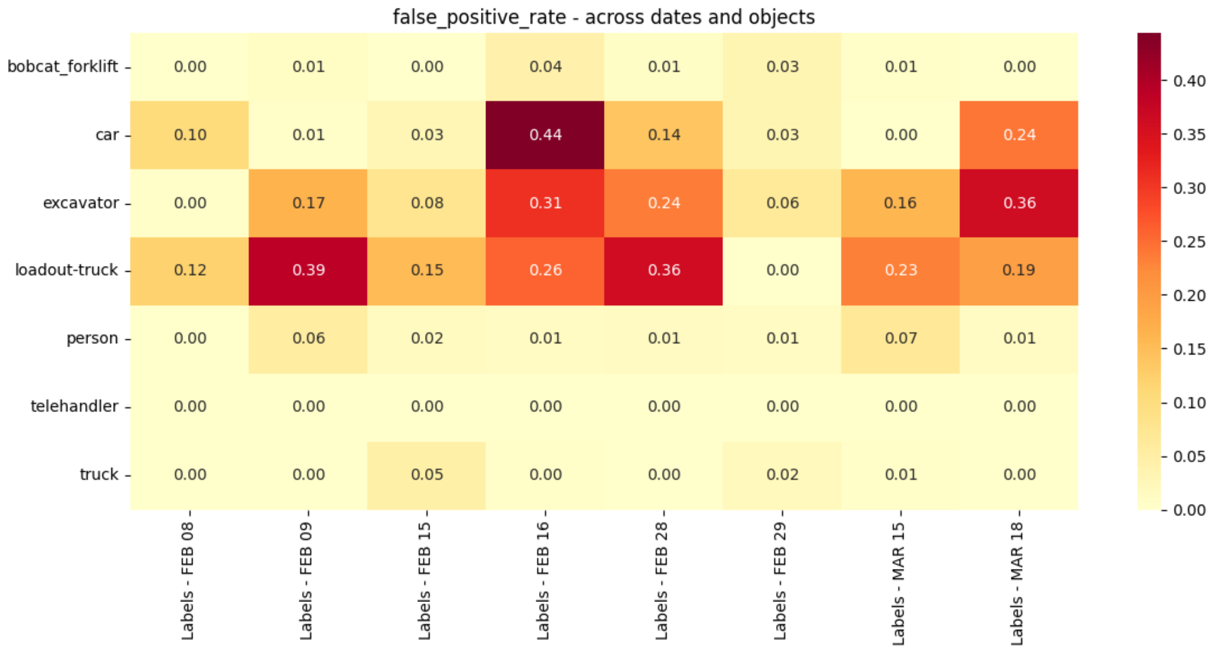


Figure 46. False Positive Rate metric to compare the performance of the AI model

Figure 46 shows the false positive rate (FPR) across different dates and object categories, showing how often the model incorrectly identifies objects that aren't present. Cars and excavators show concerning patterns of false positives, with cars reaching a high FPR of 0.44 on 16 Feb and maintaining notable rates on 18 Mar (0.24). In contrast, excavators show increasing false positives towards later dates (peaking at 0.36 on 18 Mar). Loadout-trucks demonstrate variable but significant false positive rates, with peaks of 0.39 (9 Feb) and 0.36 (28 Feb). In contrast, person detection maintains consistently low false positive rates (mostly below 0.07) across all dates, suggesting reliable performance in avoiding false person detections. Telehandlers show perfect performance with zero false positives throughout, though this might be due to their rare occurrence. Trucks and bobcat forklifts generally maintain low false positive rates (mostly below 0.05), indicating good precision in their detection. The model shows category-dependent reliability, with vehicles (particularly cars, excavators, and loadout-trucks) being more prone to false positive detections than other categories.

Figure 47 shows the false negative rate (FNR) across dates and object categories, revealing how often the model fails to detect objects that are present. Bobcat-forklifts show significantly high false negative rates in early dates (0.82–0.84) but demonstrate dramatic improvement in later periods (dropping to 0.00–0.10). Trucks also display concerning patterns with very high FNRs on specific dates (0.73 on 9 Feb and 0.81 on 28 Feb), showing better performance in other periods. Person detection shows moderate but persistent false negative rates throughout the period (ranging from 0.17 to 0.57), indicating a consistent challenge in detecting all present persons. In contrast, cars and excavators maintain impressively low false negative rates (mostly below 0.07), suggesting reliable detection when these objects are present. Telehandlers show perfect performance (0.00 throughout), though this likely indicates their absence rather than ideal detection. Loadout-trucks generally maintain low FNRs except for one spike (0.15 on 9 Feb). Overall, the model significantly improves over time for some categories (notably bobcat forklifts), while person detection and trucks remain challenging with persistently missed detections.

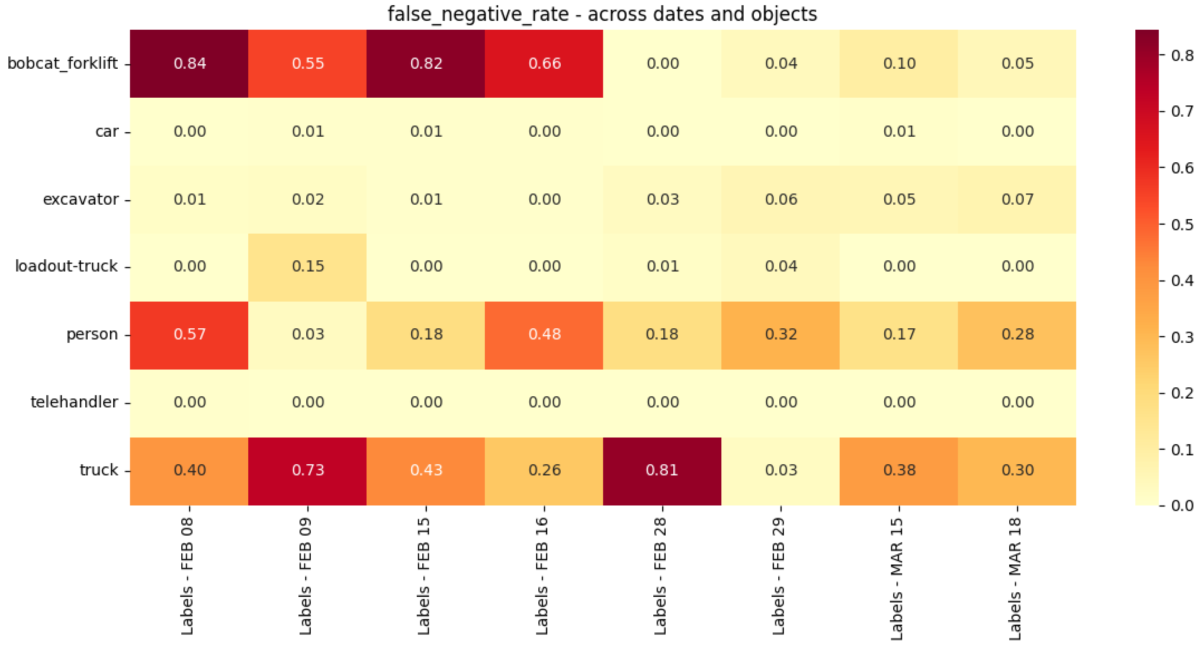


Figure 47. False Negative Rate metric to compare the performance of the AI model

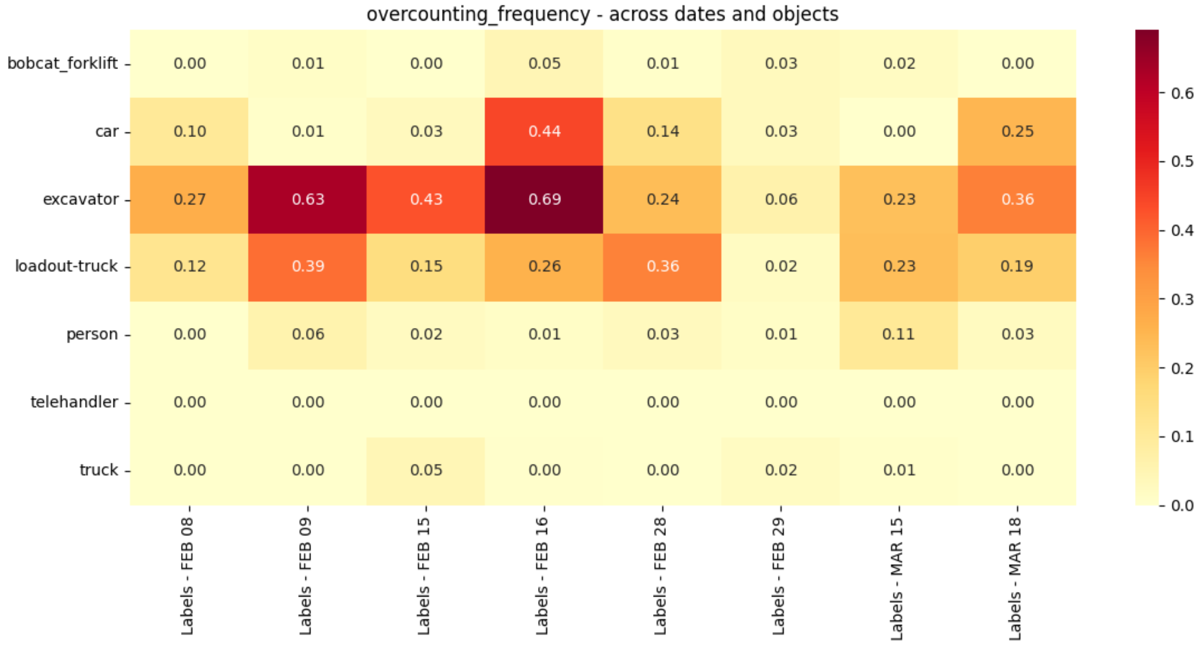


Figure 48. Overcounting Frequency metric to compare the performance of the AI model

Figure 48 shows the overcounting frequency across dates and object categories, highlighting when the model predicts more objects than actually present. Excavators show the most significant overcounting issues, with particularly high frequencies on 16 Feb (0.69) and 9 Feb (0.63) and continuing moderate overcounting in March (0.36). Cars also demonstrate notable overcounting problems, especially on 16 Feb (0.44) and 18 Mar (0.25). Loadout-trucks show consistent moderate overcounting across most dates, with peaks at 9 Feb (0.39) and 28 Feb (0.36). In contrast, person detection maintains very low overcounting frequencies (mostly below 0.11) across all dates, suggesting good precision in counting people. Telehandlers show zero overcounting throughout all dates, while trucks and bobcat forklifts maintain consistently low overcounting frequencies (mostly below 0.05). This pattern suggests that the model is particularly prone to overcounting certain vehicle types (especially excavators, cars, and loadout-trucks) while maintaining better counting accuracy for people and smaller vehicles. The temporal variation in overcounting rates might indicate changing site conditions or model performance variations across dates.

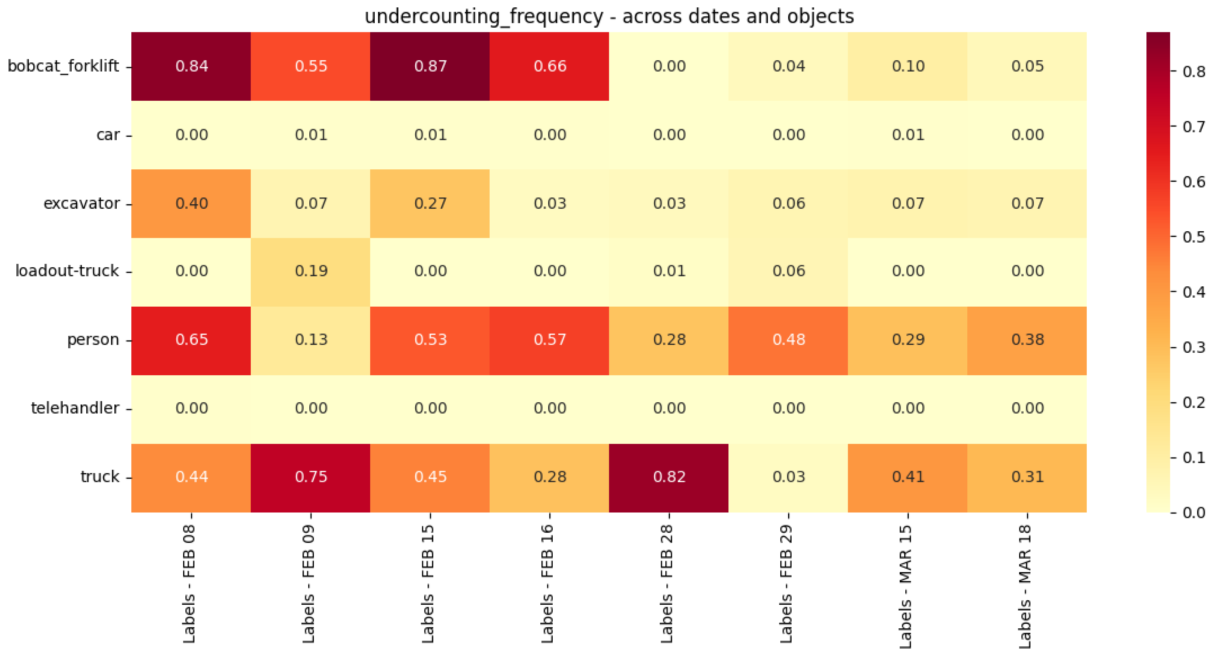


Figure 49. Undercounting Frequency metric to compare the performance of the AI model

Figure 49 shows the undercounting frequency across dates and object categories, revealing patterns where the model predicts fewer objects than present. Bobcat-forklifts show severe undercounting issues in early dates with very high frequencies (0.84–0.87) but demonstrate significant improvement in later periods (dropping to 0.00–0.10). Trucks exhibit concerning undercounting patterns, particularly on 9 Feb (0.75) and 28 Feb (0.82), though showing better performance on other dates. Person detection shows consistent moderate to high undercounting throughout the period (ranging from 0.28 to 0.65), indicating a persistent challenge in detecting all present people. Cars perform exceptionally well with minimal undercounting (mostly 0.00–0.01), while excavators show improvement over time, starting with higher undercounting (0.40 on 8 Feb) but stabilising to lower rates (around 0.07) in later periods. Telehandlers maintain zero undercounting throughout, though this likely indicates absence rather than perfect detection. Loadout-trucks generally show low undercounting except for one notable spike on 9 Feb (0.19). The temporal patterns suggest general improvement in model performance for some categories, while person detection and trucks face challenges with missed detections.

4.13 Computer Vision Challenges

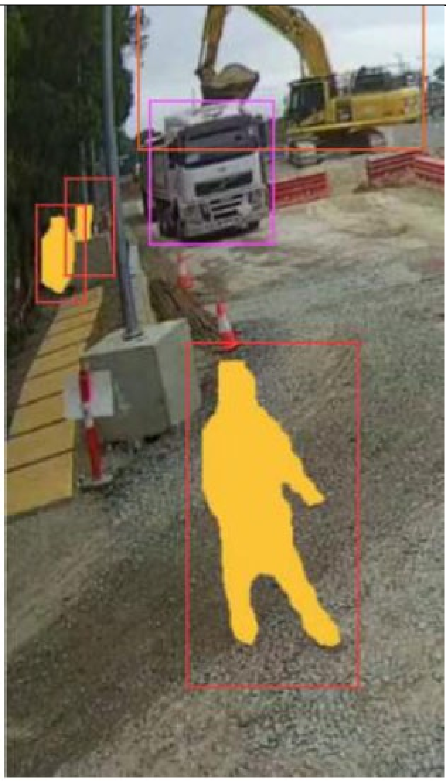
In this section, we present some of the issues and challenges that AI models may suffer due to environmental conditions (sun glares, time of the day), occlusions, and others, which may deteriorate the performance of the models. Table 25 shows some issues we identified during the data annotation and validation processes.

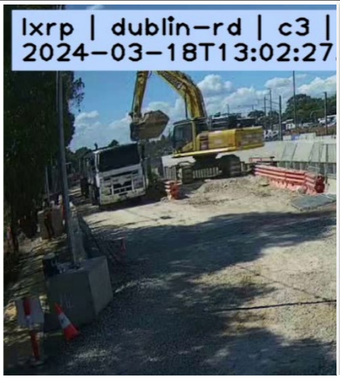
Table 25. Issues and challenges in detecting objects using computer vision models

Date and time	Description	Example image
15 Mar 2024 7 am – 8 am	Sun obscures the excavator and excavator buckets for most of this video	
15 Mar 2024 1 pm – 2 pm	Excavator bucket emptying obscured for approximately 3 buckets – expect discrepancy with Sightdata labelling	

29 Feb 2024 8:05 am	Manual labellers labelled the number of people as two, whereas AI did not pick up	
29 Feb 2024 8:35 am	Manual labellers labelled the number of people as three, whereas AI predicted only one	

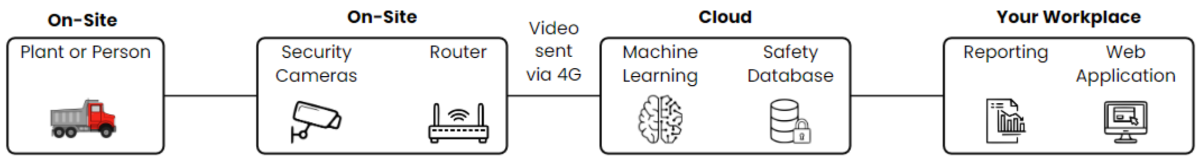
29 Feb 2024 10 am	Manual labellers labelled the number of people as three, whereas AI predicted only one Reviewer: four people are present, but only a small part of hat is visible for the fourth	
29 Feb 2024 10:05 am	Manual labeller = 3 people. AI = 1 Which person was detected by AI is not clear	

29 Feb 2024 10:50 am	Manual labeller = 3 people. AI = 1	
29 Feb 2024 11:59 am	Manual labeller = 2 people. AI = 0 Reviewer: blurred objects, maybe due to distance of objects from the camera, and/or resolution	

29 Feb 2024 4:35 pm	Manual labeller = 5 people. AI = 3 people Reviewer: 5–6 people, but panning back and forth does not make it clearer	
18 Mar 2024 1:02 pm	The safety cones were highlighted, whereas there was a worker at the back. It was a sunny day, and hence, there were a lot of shadows. These situations can trick the AI models.	

Visualisation dashboard

Sightdata has developed an easy-to-use CV system that provides EHS and logistics support to site teams. For this feasibility research study, Sightdata has adapted its safety risk and trend identification system to identify logistics metrics on construction sites in real-time.



The core of the existing system revolves around the tracking of persons and vehicles to monitor safety trends for early identification and resolution. This same principle has been adapted for logistics to enable site teams to easily track and obtain metrics for:

- Dirt Loading (Amount of dirt moved throughout the day)
- Resource Utilisation (Counts and Utilisation % over the day)
    - Plant
    - People.

Sightdata also places a key emphasis on privacy and security ensuring that all points of the system are highly secure and put the privacy of the workers first via a patented de-identification method.

Camera Gallery

The camera gallery functions like a familiar CCTV application that enables users to get an overview of all camera feeds in real-time on a singular landing page. The system uses simple new or existing cameras and 4G internet to collect, process, and deliver data in real-time to those that need to know. While also being designed with flexibility in mind and fully scalable enabling users to add or subtract an infinite number of cameras depending on user needs. This acts as the central quick-check hub for users looking to get a visual snapshot of site.

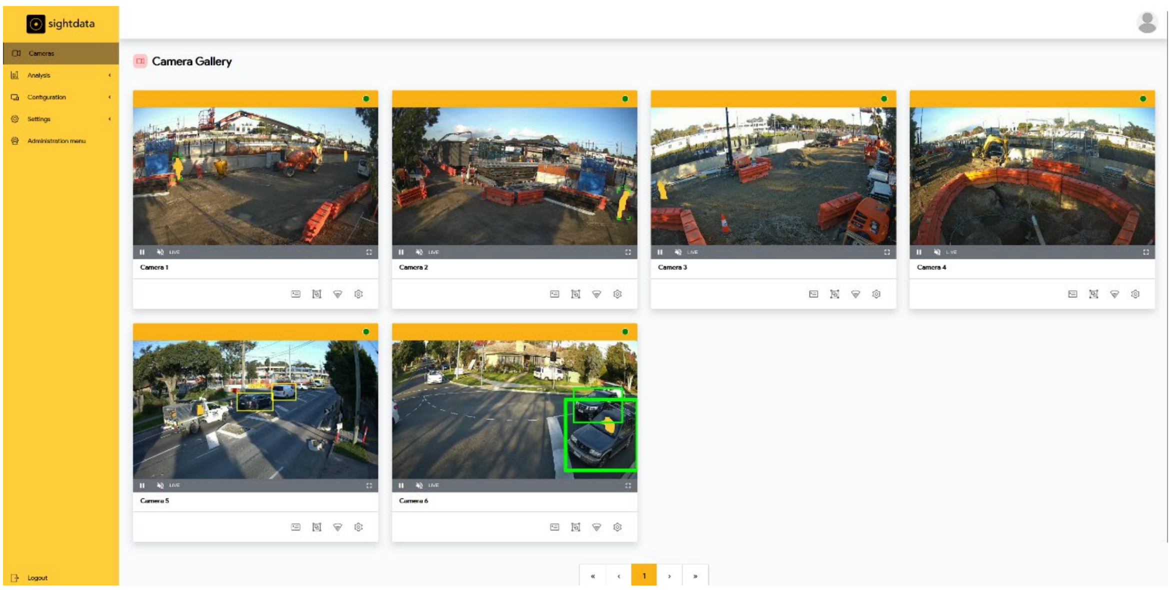


Figure 50. Sightdata Dashboard (Sightdata 2024)

However, the power of the Sightdata system works behind the scenes where these individual camera streams are processed in the cloud and have a wide range of CV and ML algorithms applied to each stream.

On a frame-by-frame basis the system identifies and classifies a large range of vehicle types (Excavator, Forklift, Car, Dirt Loading Truck, etc.) to provide counts of resources seen within frames. An additional algorithm is then applied to determine if these results are moving between frames.

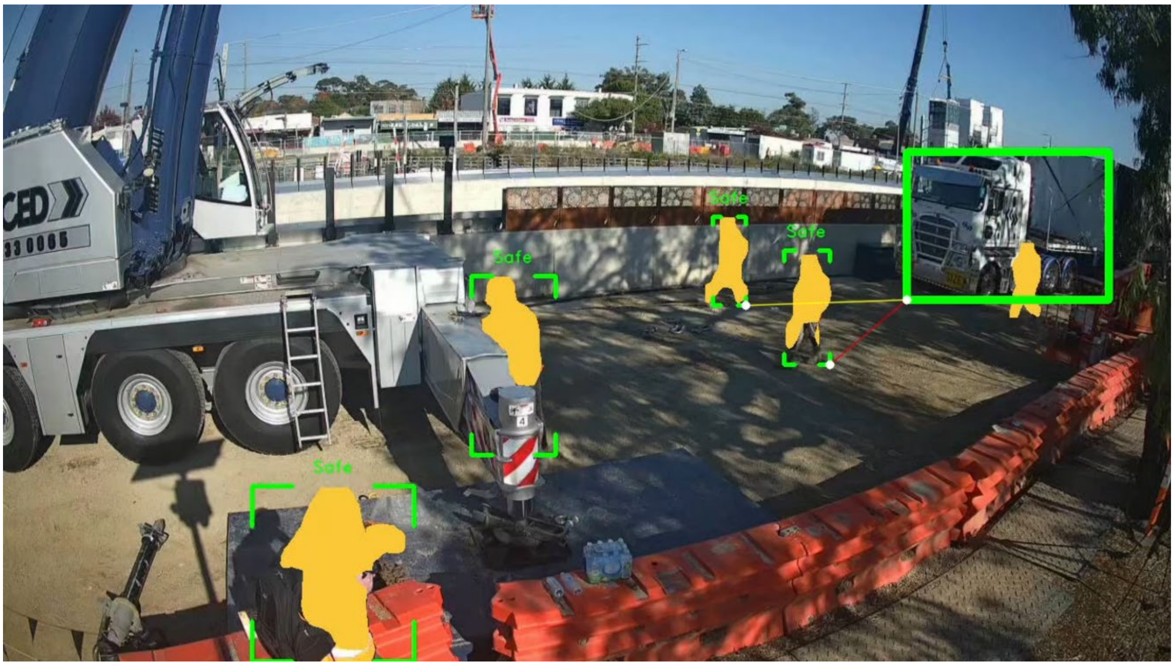


Figure 51. Example camera view (Sightdata 2024)

The data produced from these algorithms is captured frame by frame and then converted into a viewer friendly dashboard for site team review.

Dashboard Visualisations

Each section of the dashboard has been designed to identify and collect metrics for a specific use case to automate manual reporting activities. Given enough data is provided to the system it is possible to report on any visual object, typically Sightdata utilises this to provide safety alerts and trends to users but was adapted for this research study to report on logistic based metrics:

- Dirt Loading (Amount of dirt moved throughout the day)
- Resource Utilisation (Counts and Utilisation % over the day)
    - Plant
    - People.

In this early stage all dashboards are combined into a format that verifies the application of the technology. This allows for users to view a standard daily, weekly, monthly, yearly or custom date range that the dashboard will automatically update to show results for that period.

Users are also able to dive deeper into data using the line graphs to home in on data that they wish to analyse further. Excel export is also available to meet existing reporting requirements.

The visualisations shown in this report can be altered to any format users required due to the amount of data collected from each video frame.

Dirt Loading Visualisation

This module dives deeper into the classification of objects and has been separately trained to identify excavator buckets within detected excavators. A separate algorithm is then deployed to count the number of buckets loaded out of site to load-out vehicles the algorithm can determine total spoil and the time it was removed from site. A variety of visualisations have been created based off this information with the aim of providing different insights into the dirt loadout metrics that have been collected:

- Daily Count of Buckets
    - Displays a bar graph showing amount of spoil removed (y-axis) from site over time (x-axis) fixed to show '1 day' as the lowest bar on the bar chart
    - Users can highlight a specific date range within the graph to automatically adjust the date range of the overall dashboard and dive deeper into a smaller range of information
- Total Buckets unloaded
    - Displays overall counts of spoil removed per camera as a count
    - Users can view this and obtain a quick snapshot of overall metrics relating to dirt loading per on-site area
- Buckets Unloaded per Camera
    - Displays overall % of spoil removed against other cameras as a pie graph
    - Users can view this and obtain a quick snapshot of each area's removal statistics against the other project areas
- Detailed Count of Bucket Unloads
    - Displays a bar graph showing amount of spoil removed (y-axis) from site over time (x-axis). No lower limit is applied to this graph and can show detail down to 1 minute bar interval
    - Users can dive deeper into daily spoil removal metrics and get a snapshot of spoil loadout activities down to a 1-minute interval.

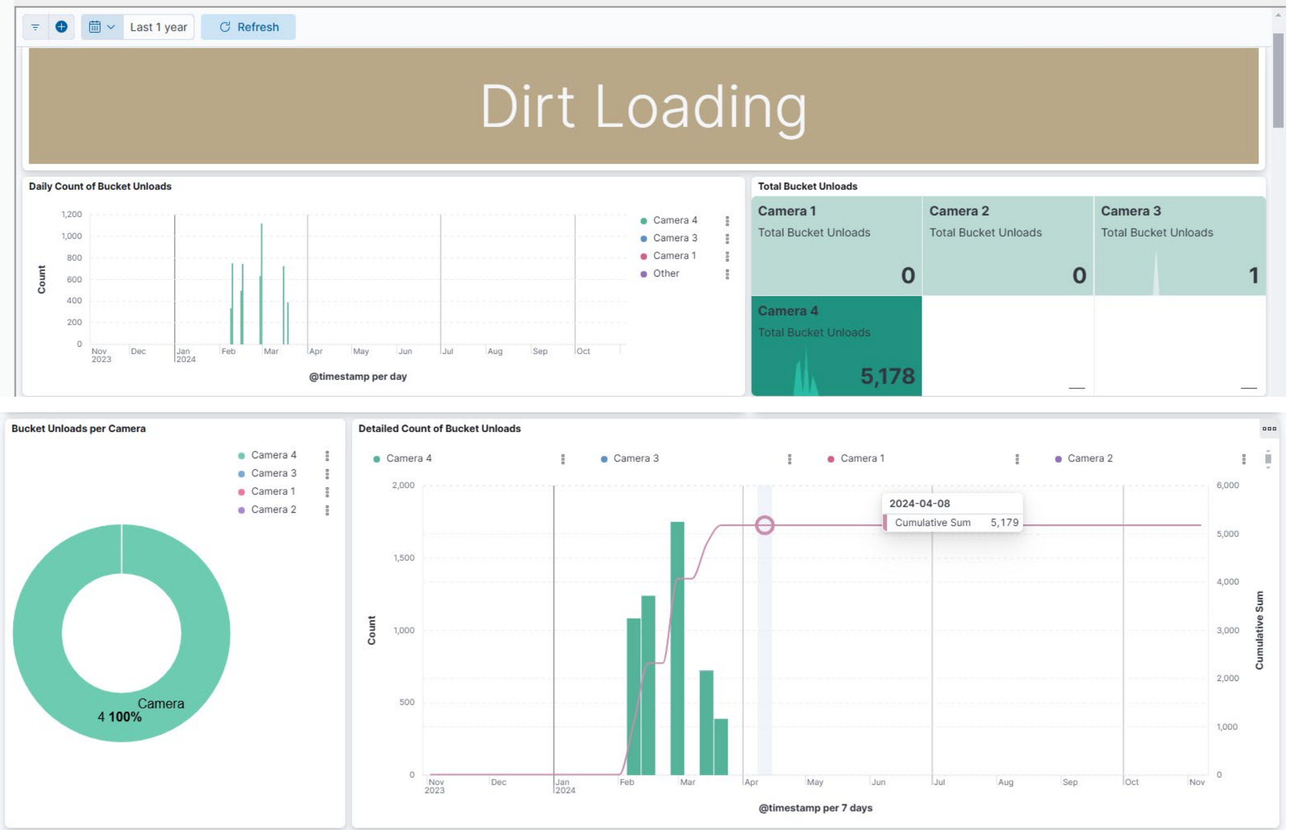


Figure 52. Dirt Loading Dashboard (Sightdata 2024)

Resource Utilisation Visualisation

This module enables users to obtain a quick snapshot of plant and worker counts in work areas throughout any time period of the project. An additional algorithm is also implemented to determine standdown and active time for machinery detected onsite.

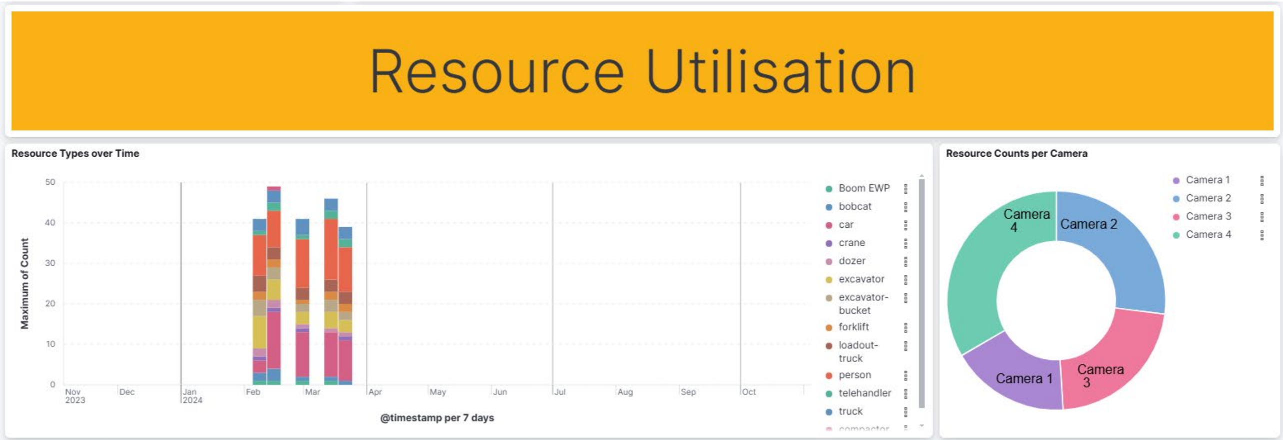


Figure 53. Resource Utilisation Dashboard (Sightdata 2024)

Resource Utilisation -–Vehicles:

The Sightdata vehicle detection module is trained to differentiate between a variety of common industrial plant for analysis:

- Bobcat
- Car
- Crane
- Dozer
- Excavator
- Excavator-bucket
- Forklift
- Loadout-truck
- Person
- Telehandler
- Truck
- Boom EWP
- Compactor.

These vehicle types can be filtered in and out of the dashboard meaning that users can single out multiple vehicle types they are interested in or see a snapshot of all onsite plant.

An additional algorithm is also then applied over the top to not only count the number of each vehicle type that is detected but also determine if the vehicle is on motion or stationary. A variety of visualisations have been created based off this information with the aim of providing different insights into the dirt loadout metrics that have been collected:

- Vehicles over time
    - Displays a bar graph showing amount of the count of vehicles detected (y-axis) from site over time (x-axis). This has been created so that users can filter cameras in and out to view metrics for different areas
    - Users can highlight a specific date range within the graph to automatically adjust the date range of the overall dashboard and dive deeper into a smaller range of information
- Vehicle motion over time
    - Displays a % bar chart every 30 mins that shows a quick snapshot of the total of time vehicles spent moving or stationary within that 30 mins
    - Users can view this and obtain a quick snapshot of what proportion of vehicles are moving vs stationary in the area
- Vehicle Time Stationary and in Motion
    - Displays an overall total of if vehicles were moving or stationary onsite for that time period
    - Users can view this and obtain a quick snapshot of what proportion of vehicles are moving vs stationary in the area.

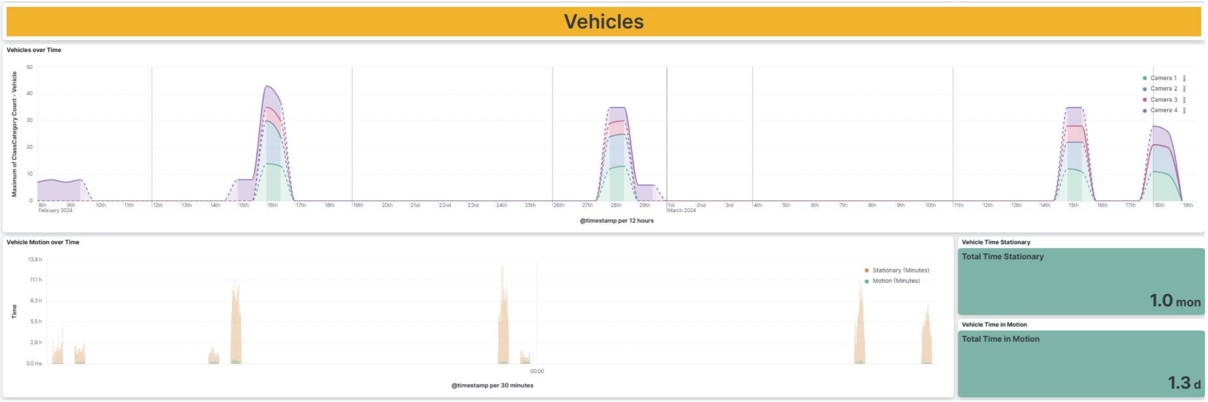


Figure 54. Vehicle count example (Sightdata 2024)

Resource Utilisation – People:

Sightdata's person detection algorithm de-identifies individuals via the introduction of an orange blob like figure to mask the persons perimeter. From there the algorithm can take privacy conscious counts of persons onscreen and feed this information into the dashboard to provide accurate counts of persons in work zones.

Figure 55. People count example (Sightdata 2024)

- People over time
  - Displays a bar graph showing amount of the count of vehicles detected (y-axis) from site over time (x-axis). This has been created so that users can filter cameras in and out to view metrics for different areas
  - Users can highlight a specific date range within the graph to automatically adjust the date range of the overall dashboard and dive deeper into a smaller range of information.

Dashboard Analytics

Individually the previous metrics are useful for site teams for reporting and will result in decreased manual hours previously assigned to tedious and costly tracking exercises.

However, when different data sets are compared against each other and analysed the insights gained from this information can be invaluable. Enabling a quick visualisation for site teams to effectively analyse higher-order site trends and metrics.

Figure 56. Dashboard analytics example (Sightdata 2024)

The below examples can aid decision making and identify inefficiencies previously going unnoticed on projects:

Visualisation of trucks

The number of detected trucks can be plotted against trucks that were being involved in load-out activities and identify inefficiencies in spoil loadout.

From looking at this graph users could tell that the maximum amount of trucks being loaded out at any one time is 4–5 trucks and that unnecessary hours are being spent by trucks drivers if more than five arrive.

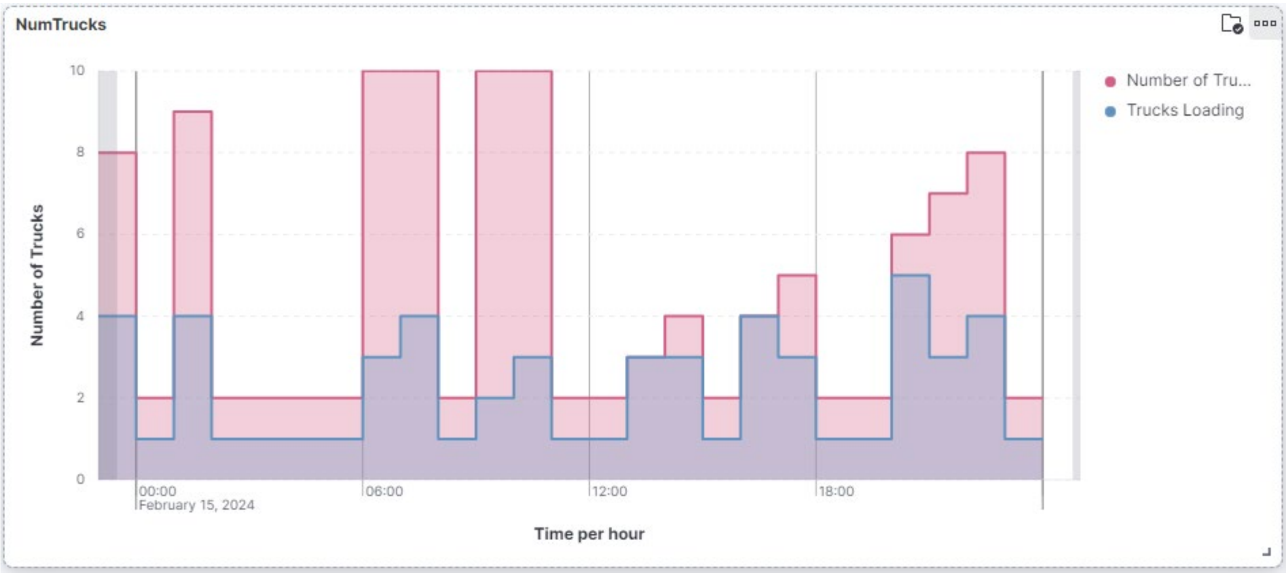


Figure 57. Truck counts (Sightdata 2024)

Visualisation of Soil Volume vs Moving Excavators

The number of moving excavators in the area can be plotted against the total volume of dirt that was loaded out in that period.

From looking at this graph users could identify increased or decreased needs for excavators depending on soil volume removal rates the project is aiming for.

Figure 58. Excavator movement (Sightdata 2024)

Visualisation of the Number of Excavators

The number of detected excavators can be plotted against the number of moving excavators seen in the area.

From looking at this graph users can identify utilisation of plant onsite and if machinery can be off hired if it is no longer required.

Figure 59. Number of excavators (Sightdata 2024)

Visualisation of the Number of Workers

The number of workers onsite can be plotted against a variety of metrics to gain insights into the project areas metrics.

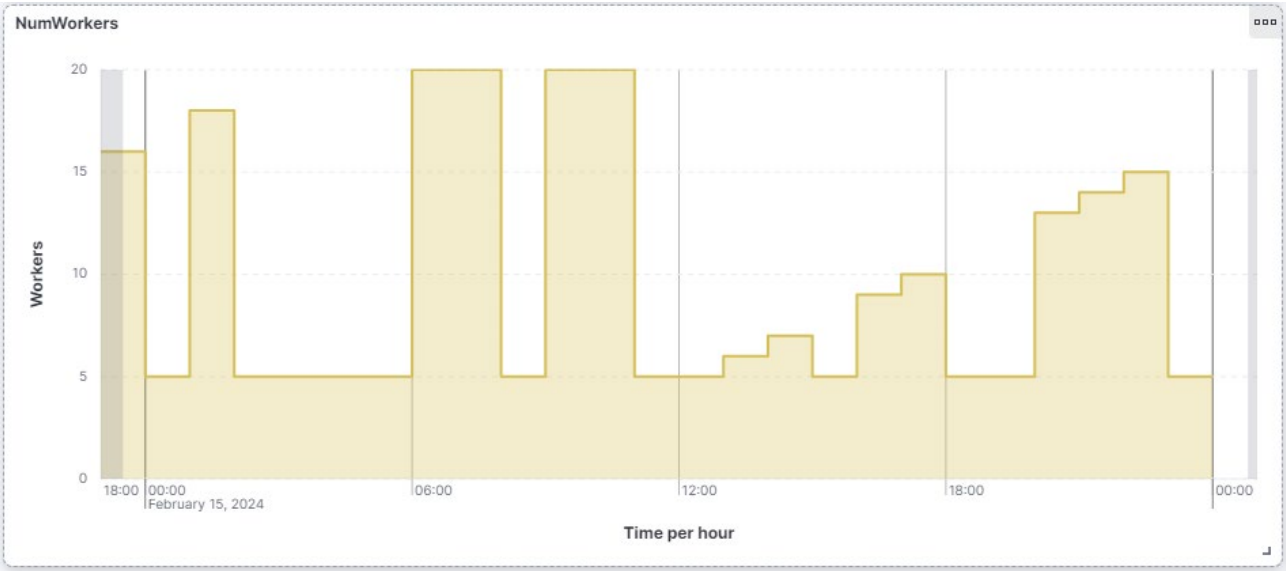


Figure 60. Number of workers (Sightdata 2024)

- Visualisation of the soil volume against rain and temperature

The Sightdata system is also able to pull in rain and temperature information for comparison against area metrics to easily draw comparison of site conditions and its effect on work activities. For example, low spoil loadout could be due to inclement weather that resulted in cancelled work activities.

Figure 61. Visualisation of soil volume, rain and temperature

Collected Results

Results of key loadout dates from onsite works can be found below. Throughout the research study multiple data training runs have been implemented each increasing the accuracy of the system. Over a longer time period, it is theorised that 99% accuracy can be achieved.

Note: No filter is applied to vehicles in these screenshots, so a range of parked cars and utes have caused a dramatic vehicle stationary time in results. Results for 8 Feb are presented in subsequent pages with a full series of results for select days in Appendix G.

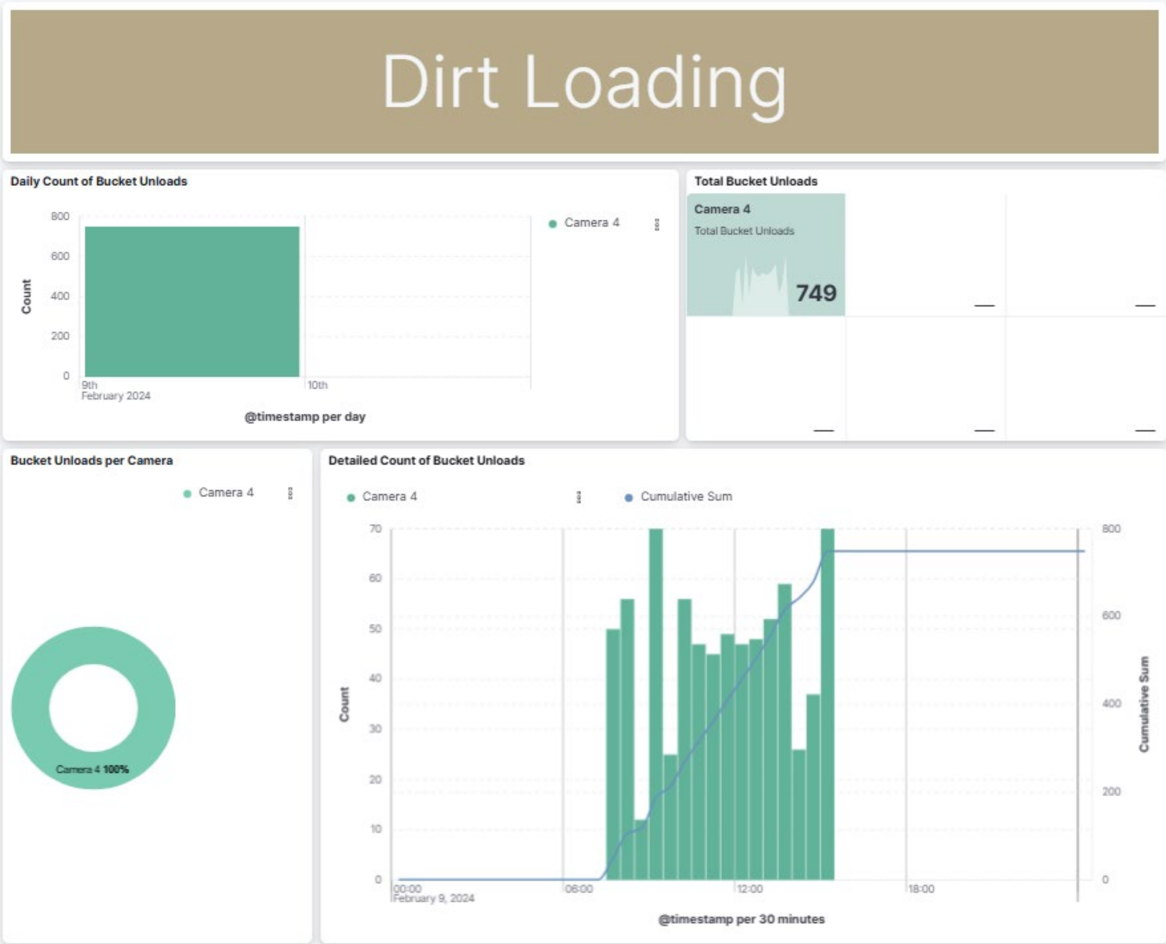


Figure 62. Dirt Loading 9 Feb 2024 (Sightdata 2024)

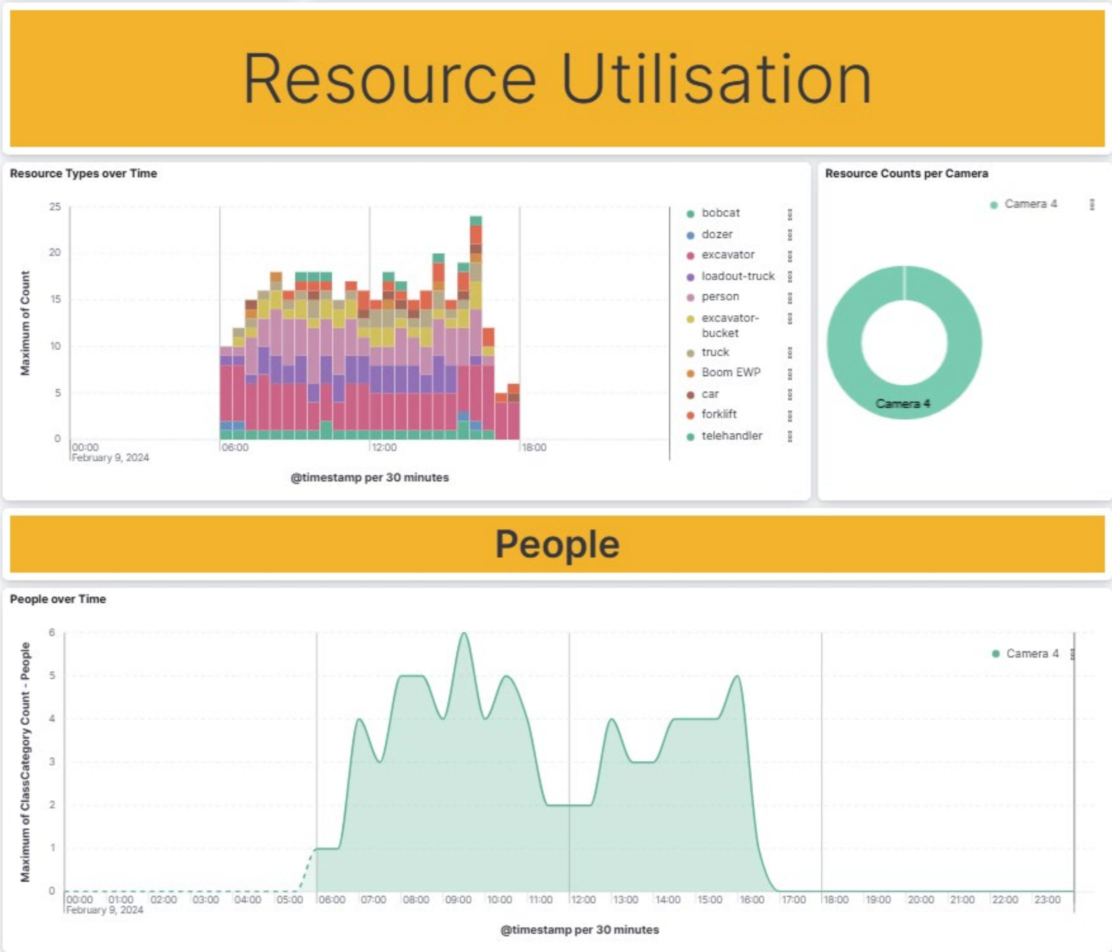


Figure 63. Resources 9 Feb 2024 (Sightdata 2024)

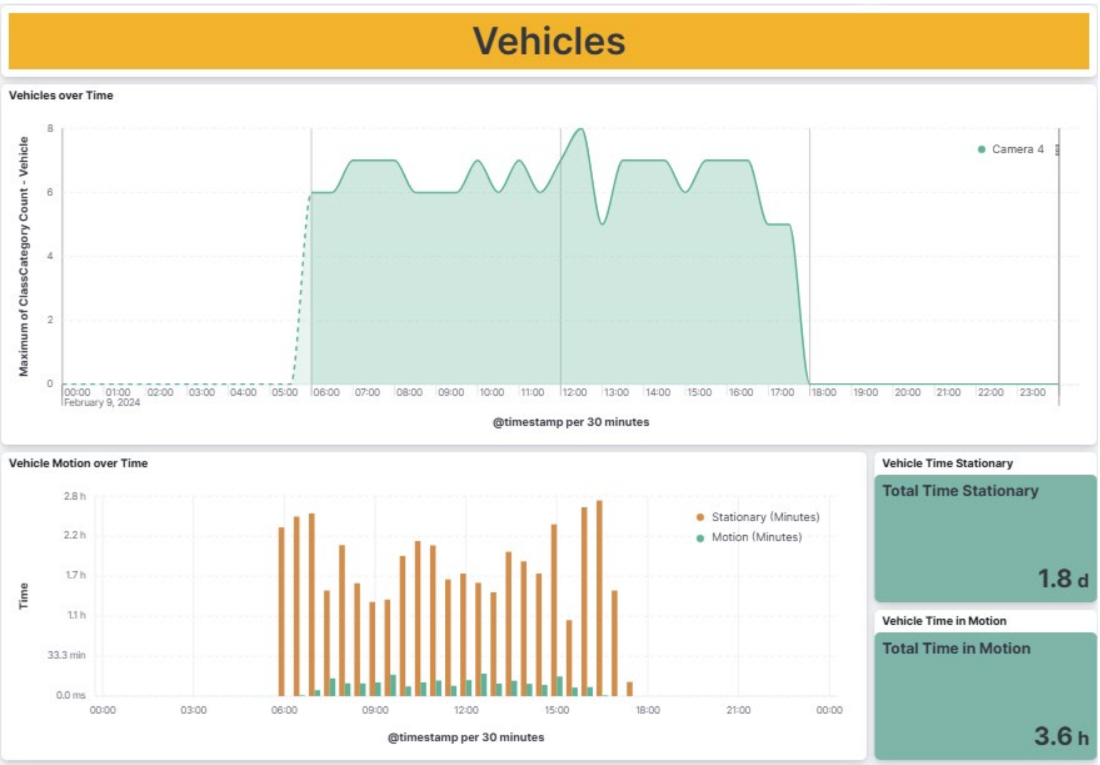


Figure 64. Vehicles 9 Feb 2024 (Sightdata 2024)

5. IMPLEMENTATION ON CONSTRUCTION SITES

Implementation on construction sites is complex and involves significant logistics and stakeholder engagement to ensure all parties understand the work that is being done and the privacy controls in place. Below is a list of key stakeholders for this trial:

1. **Level Crossing Removal Project (LXRP)**

   Key Concerns: Overseeing overall project progress, ensuring compliance with safety standards, and achieving productivity benchmarks. LXRP focuses on managing the integration of AI and computer vision technologies to monitor productivity.

2. **The University of Melbourne**

   Key Concerns: Ensuring the academic and research validity of computer vision models applied in the project. The university team is committed to data accuracy, producing valuable insights, and generating reliable results that could support future academic studies and industry applications.

3. **Sightdata (Data and Technology Provider)**

   Key Concerns: Maintaining the reliability and accuracy of data collection systems, upholding data privacy standards, and ensuring that AI and computer vision technologies comply with LXRP's productivity metrics and operational goals.

4. **Project Managers and Alliance Representatives**

   Key Concerns and Responsibilities: Managing project timelines, budgets, and resource allocation. They oversee on-site data collection activities, including tracking truck and trailer counts and earthwork removal volumes.

5. **Workers**

   Key Concerns: Ensuring safe working conditions, job security, and fair labour practices, while advocating for the responsible adoption of technologies that safeguard worker welfare and employment stability.

5.1 Key challenges faced by the construction sector in adopting digital technologies

Technological Challenges (Soltani et al., 2023)

- **High Costs of Implementation:** Implementing digital technologies, such as Building Information Modelling (BIM) and the Internet of Things (IoT), often requires substantial investment. Many companies, especially small and medium enterprises (SMEs), may find these costs prohibitive. The initial outlay for hardware, software, and training can be a significant barrier, making it difficult for smaller firms to keep pace with larger competitors.
- **Interoperability Issues:** The construction industry features disparate software systems that often do not communicate effectively with each other. This lack of interoperability can lead to inefficiencies and additional costs for upgrading or changing systems to ensure compatibility. Without seamless integration, the full benefits of digital technologies cannot be realised, leading to fragmented workflows and potential data silos.

- **Lack of Infrastructure:** Many construction companies lack the necessary technological infrastructure to support the adoption of IR 4.0 technologies. This includes both hardware and software capabilities. The absence of a robust technological foundation makes it challenging to implement advanced digital tools and systems effectively.

Organisational Challenges

- **Fragmented Industry Structure:** The traditional and fragmented structure of the construction industry impedes the seamless adoption of new technologies. Different stakeholders, such as designers, contractors, and suppliers, often work in silos, leading to coordination challenges. This fragmentation can hinder the flow of information and slow down the adoption of integrated digital solutions.
- **Resistance to Change:** There is significant resistance to change within the construction industry. Many stakeholders are hesitant to adopt new technologies due to a lack of understanding of their benefits and potential impacts. This resistance is often rooted in a preference for established practices and a reluctance to invest in unfamiliar tools.
- **Lack of Skilled Workforce:** The industry faces a shortage of skilled workers who are proficient in using advanced digital technologies. This skills gap makes it challenging to implement and effectively utilise new technologies. Without adequate training and development, the workforce may struggle to adapt to the demands of digital transformation.
- **Leadership and Management Issues:** Poor leadership and inadequate management attitudes toward digital innovation are barriers to technology adoption. There is often a lack of vision and commitment from top management to drive digital transformation. Effective leadership is crucial for fostering a culture that embraces change and innovation.

Data-Related Challenges

- **Data Collection and Quality Issues:** Effective adoption of digital technologies requires high-quality data collection and management. However, challenges in ensuring data accuracy, completeness, and reliability can hinder technology implementation. Inaccurate or incomplete data can compromise the effectiveness of digital tools and lead to suboptimal decision-making.
- **Data Security and Privacy Concerns:** The increased use of digital technologies raises concerns about data security and privacy. Ensuring robust data protection measures is critical to gaining stakeholders' trust. Breaches of data security can have severe consequences, including legal ramifications and damage to a company’s reputation.

Social and Cultural Challenges

- **Cultural Barriers and Implicit Biases:** The construction industry is traditionally male-dominated and resistant to cultural changes. Implicit biases based on gender and race can impact the adoption of new technologies and the creation of inclusive work environments. Overcoming these biases is essential for fostering a diverse and innovative workforce.
- **Generational Resistance:** Older workers in the industry may be reluctant to adopt new technologies due to a lack of familiarity and comfort with digital tools. This generational resistance can slow down the pace of digital transformation. Bridging

the gap between different age groups within the workforce is crucial for successful technology adoption.

Policy and Regulatory Challenges

- **Lack of Legislative Mandates:** The absence of legislative mandates and standardised regulations for adopting IR 4.0 technologies in the construction industry complicates the adoption process. Clear policies and guidelines are needed to support and incentivise digital transformation. Without regulatory frameworks, there is less pressure on companies to innovate and adopt new technologies.
- **Need for Regulatory Compliance:** Ensuring compliance with various regulatory requirements, including data protection and safety standards, is essential. The lack of clear regulatory frameworks can create uncertainties and hinder the adoption of digital technologies. Establishing comprehensive regulations will provide a clearer path for companies to follow and encourage broader adoption of innovative solutions.

5.2 Implementation guides to approach to engaging stakeholders

1. **Provide a comprehensive justification for the implementation of innovative practices in the business:**

   To secure the endorsement of the for Industry 4.0 technologies, it is crucial to provide a persuasive rationale that emphasises the concrete advantages. Utilise case studies and success stories from previous construction projects to demonstrate advancements in safety, productivity, and financial savings (McKinsey Global Institute, 2017). Present comprehensive data and return on investment (ROI) analyses to demonstrate the financial advantages, thereby compelling the adoption of new technologies.

2. **Communicate and build relationships**

   It is crucial to develop trust and establish open lines of communication with the leadership and members of key stakeholder. Arrange frequent meetings to explore the possibilities of cutting-edge technologies and resolve any apprehensions. Conduct workshops and seminars that specifically address the advantages and application of Industry 4.0 technologies. Invite industry professionals and technology providers to share their expertise. Establish online forums exclusively for workers to express their viewpoints and offer input on proposed advancements, guaranteeing a comprehensive and all-encompassing approach.

3. **Develop Pilot Projects and Demonstration Sites**

   Demonstrating the tangible implementation and advantages of emerging technologies through trial initiatives is exceedingly impactful. Identify and choose a small number of prominent pilot projects where Industry 4.0 technologies can be applied. Establish exhibition sites where workers can observe the technologies being utilised, offering practical experience and instruction. Record and distribute the results of these trial initiatives to workers to instil trust in these innovative technologies.

4. **Provide Comprehensive Training and Education**

   It is essential to provide workers with the necessary knowledge and skills to effectively utilise and gain advantages from emerging technologies. Create customised training programmes designed specifically for workers, with a strong emphasis on practical skills and safety protocols associated with Industry 4.0 technologies. Establish partnerships with universities, technical institutes, and vocational training centres to provide accredited courses. Implement a system of ongoing educational opportunities to ensure that workers remain informed about the most recent advancements.

6. PROJECT FINDINGS

Bucket Counting: The AI model demonstrates strong performance in counting bucket loads of dirt across five days during February and March 2024, with accuracy rates ranging from 89% to 99%. The system generally shows high reliability, with most days achieving above 95% accuracy, though there are occasional significant deviations, as seen on 15 March, when the overcounting rate reached 10.89%. The hourly analysis reveals that while the model can track daily totals well, it may miss or overcount during specific hours, such as the substantial undercounting observed between 7:00-8:00 am on 18 March (16 predicted vs 45 actual). The AI system could provide reliable daily aggregate measurements of earth-moving operations for construction site productivity monitoring. However, real-time hourly productivity tracking might need additional validation or refinement.

Loadout Vehicle Counting: The AI model demonstrates consistent performance in counting number of trucks leaving the site with maximum errors in the range of +- 5%. Although this was deemed accurate by the team it is recommended that earthwork monitoring be performed using the bucket counting method as it is less reliant on potentially inaccurate assumptions around volumes in each truck/ truck trailer combination. This can lead to inaccuracies in estimation of volumes moved which was found to be the case for several days in this trial.

People Counting: Based on the analysis comparing AI predictions against manual annotations across eight days in early 2024, the computer vision model shows a promising solution but needs performance improvements for people counting. Although the MAE remains consistently low (0.11–0.35), suggesting reasonable accuracy, the model exhibits a systematic tendency to undercount people, as evidenced by the negative cumulative differences across all dates and higher undercounting rates (4–12%) compared to overcounting rates (0.28–7%). The undercounting becomes more pronounced as the number of people increases, with errors reaching up to two people fewer than actual counts when four people are present. For construction site productivity monitoring, this suggests the AI system would provide a conservative estimate of site occupancy, though its reliability decreases with larger groups present.

Object Detection: The AI model's performance detecting construction site objects varies significantly across different object categories. The exact accuracy improved notably after model retraining in mid-February, with most object categories achieving high within-one accuracy (above 0.90). However, distinct patterns emerge in detection challenges: person detection consistently shows undercounting issues (37–48% undercounting rate). Still, it maintains low false positives; vehicles like excavators tend toward overcounting (up to 69% overcounting frequency), and smaller equipment like bobcat-forklifts showed marked improvement over time. The model performs best during low-activity periods and struggles during peak hours (10:00 am – 2:00 pm), mainly when dealing with multiple objects simultaneously. For construction site productivity monitoring, this suggests the system can provide reliable tracking of general site activity patterns and vehicle movements. However, real-time counts during busy periods may require additional verification, especially for person counts and when multiple vehicles are present.

Limitations of Existing Manual Data Collection were particularly evident with data duplication between zones and inaccurate assumptions relating to earthwork volumes places in trucks The **Labour-Intensive** manual process was also susceptible to delays in reporting, something that was not an issue for the computer vision dashboard. This can cause inefficiencies in tracking and reporting, ultimately impacting operational timelines and project costs.

Finally particular challenges were encountered when Implementing Computer Vision on Construction Sites including stakeholder pushback (such as worker resistance), data quality and environmental factors including the inconsistent video quality for example footage impacted by solar glare and occlusion. Complex equipment interactions also including the diverse range of machinery used on construction sites adds complexity to automated tracking efforts.

7. RECOMMENDATIONS

Recommendations have been broken down into installation and stakeholder engagement categories as follows:

Installation Recommendations

- Installing cameras at heights of approximately eight metres on site would provide a clearer (normalised) view of workers, equipment and plant and placed at entrance and exits on the site. This view makes the objects captured relatively better (objects appear similar) and reduces the chances of AI missing objects or objects appearing too large.
- Installing cameras at higher heights also reduces the chances of occlusions, shadows, accidental tipping, and other issues, improving the capability of AI algorithms. This also reduces workers' concerns about monitoring and privacy with cameras at a greater distance and not positioned at eye level.
- Maintaining at least 1080p resolution will improve recognition at greater distances and provides a better balance between detail and bandwidth than 720p. At 1080p, you can reliably detect and identify objects at medium distances while managing data storage efficiently. H.265+ compression is also strongly recommended within camera specifications as it reduces bandwidth by up to 50% compared to standard H.265, allowing you to maintain higher resolution and frame rates without overwhelming your storage systems. A hybrid approach to camera deployment could also be used with high-resolution overview cameras (3840×2160) positioned at elevated points to provide comprehensive site coverage, while strategically placed 1080p cameras can monitor specific high-activity areas.
- Sun-glares and illuminations are significant issues for AI algorithms. Positioning cameras at height and then pointing them downwards from a height (40 to 60 degrees from the vertical axis) also reduces the issue of cameras directly encountering sun-glares, thereby improving AI's capabilities.
- Inclusion of a 'health' monitoring and notification system for the cameras such as monitoring of battery voltage or downtimes would assist in identifying and minimising data loss. For critical monitoring implementing a comprehensive backup and failover system is recommended for robust data protection and system reliability. This could include redundant power supplies, local storage backup and auto sync measures to ensure any data missed during network outages is uploaded once connections are re-established.
- Installing GPS sensors along with cameras or having cameras with GPS onboard will eliminate the timestamping errors as GPS receivers provide highly precise timestamps every second. The GPS timestamps can be integrated along with video data to establish a foolproof mechanism of time events on-site, thereby reducing prediction and annotation errors.

Stakeholder Engagement and Privacy Recommendations

- Necessary preliminary stakeholder engagement with a focus on the site teams and workers. Potential of broader governance structure recommendations for example a board that oversees the use of the data.
- Continuing of blanking out personnel on Sightdata platform to ensure worker privacy.
- Include QR codes on camera poles that link to a webpage explaining privacy controls and what the cameras are being used for.
- Training and information relating to the use of the tools for site crews to ensure teams understand the application of the onsite cameras.

8. FUTURE APPLICATIONS

Cumulative Metrics

Future applications of AI and machine learning could enable automated tracking of personnel, equipment, and activities on-site, monitoring cumulative metrics like total shifts, equipment usage, and worker hours. AI could also enhance safety by detecting required safety gear in real-time. These applications would turn footage into actionable insights, allowing managers to improve productivity, allocate resources efficiently, and ensure a safer work environment as detailed in **Table 26**.

Table 26. Cumulative metrics of benefit in future iterations

Metric	Description	Data Type
Total Number of Shifts	Cumulative count of shifts monitored within the camera's field of view over the selected time window.	Count
Total Number of People	Sum of all individuals detected within the camera's field of view over the time window.	Count
Average Number of People per Shift	Average count of individuals detected per shift within the camera's field of view.	Average Count
Total Hours of People	Sum of all hours worked by the individuals detected within the camera's field of view over the time window.	Hours (total)
Average Hours of People per Shift	Average number of hours worked by individuals per shift within the camera's field of view.	Hours (average)
Total Number of Equipment (Per Type)	Cumulative count of each type of equipment (e.g., excavators, dozers) detected within the camera's field of view.	Total count per type
Total Equipment Uptime (Per Type)	Total operational hours for each type of equipment detected within the camera's field of view.	Hours (total per equipment type)
Total Equipment Uptime (For Each Equipment)	Total operational hours for individual equipment units (e.g., Excavator 1, Dozer A) detected within the camera's field of view.	Hours (total per individual equipment)

Combined Metrics

To effectively manage and analyse the earthwork removal process, using a combination of time series and cumulative metrics, which provides a robust set of analysis tools that enhance decision-making capabilities. By integrating detailed, real-time observations from time series metrics with broad overviews from cumulative metrics, they gain a deeper insight into the project's progression. This dual approach supports both day-to-day and long-term strategic management. Additionally, to handle this combined data effectively from all cameras on the site, a structured approach to aggregating metrics across multiple viewpoints is crucial. This ensures that data from different locations are integrated smoothly, providing a comprehensive and cohesive analysis of the entire project as shown in Table 27.

Table 27. Combined metrics of benefit in future iterations

Combined Metric	Description	Data Collection Method
Total Number of Equipment (Per Equipment Type)	Cumulative count of each type of equipment (e.g., excavators, dozers) detected by all cameras across the site.	Cumulative Metric
Total Equipment Uptime or Utilisation (Per Equipment Type)	Sum of operational hours for each type of equipment (e.g., total hours for all excavators) detected by all cameras.	Time Series Metric Combined with Cumulative Data
Total Equipment Uptime or Utilisation (For Each Equipment)	Sum of operational hours for individual equipment units (e.g., Excavator 1, Dozer A) as detected by all cameras	Time Series Metric Combined with Cumulative Data

The computer vision and AI techniques developed specifically for productivity monitoring of earthwork can be extended to other earthwork sites. These metrics can be applied to other types of monitoring by modifying the metrics so that the core of the AI techniques can be leveraged at multiple sites with minimal changes. For example, computer vision technology can play a significant role in ensuring that these projects adhere to environmental standards and regulations effectively (Waste Management of EPA). The use of computer vision to automatically identify and capture excavator types and bucket sizes, track equipment usage in real-time on a dashboard with assigned labels as discussed in the cumulative metrics section will also add significant value to the productivity monitoring and improve equipment efficiency.

Implementing a system that links dashboard camera footage with corresponding timestamps to hyperlinked video footage would further improve the useability of the dashboard. This feature would allow users to click on specific timestamps on the dashboard, instantly bringing up the recorded video captured on-site, thereby providing a more detailed and visual record of the work being performed ensuring that the site team can gain rapid insights into the performance of the project.

REFERENCES

Abioye, S. O., Oyedele, L. O., Akanbi, L., Ajayi, A., Davila Delgado, J. M., Bilal, M., Akinade, O. O., & Ahmed, A. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. Journal of Building Engineering, 44, 103299. https://doi.org/10.1016/j.jobe.2021.103299

Azar, E. R. (2016). Construction Equipment Identification Using Marker-Based Recognition and an Active Zoom Camera. Journal of Computing in Civil Engineering, 30(3), 04015033. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000507

Brett Long 2024. Existing Productivity and Benchmarking Practices. Confluence.

Bügler, M., Borrmann, A., Ogunmakin, G., Vela, P. A., & Teizer, J. (2017). Fusion of Photogrammetry and Video Analysis for Productivity Assessment of Earthwork Processes. Computer-Aided Civil and Infrastructure Engineering, 32(2), 107–123. https://doi.org/10.1111/mice.12235

Bügler, M., Ongunmakin, G., Teizer, J., Vela, P. A., & Borrmann, A. (2014). A comprehensive methodology for vision-based progress and activity estimation of excavation processes for productivity assessment. Proc. of the EG-ICE Workshop on Intelligent Computing in Engineering, 1, 1–10.

Chen, C., Zhu, Z., & Hammad, A. (2020). Automated excavators activity recognition and productivity analysis from construction site surveillance videos. Automation in Construction, 110, 103045. https://doi.org/10.1016/j.autcon.2019.103045

Chen, C., Zhu, Z., & Hammad, A. (2022). Critical Review and Road Map of Automated Methods for Earthmoving Equipment Productivity Monitoring. Journal of Computing in Civil Engineering, 36(3), 03122001. https://doi.org/10.1061/(ASCE)CP.1943-5487.0001017

Chi, S., & Caldas, C. H. (2011). Automated Object Identification Using Optical Video Cameras on Construction Sites. Computer-Aided Civil and Infrastructure Engineering, 26(5), 368–380. https://doi.org/10.1111/j.1467-8667.2010.00690.x

Davidson, S. 2017. How much is a cubic metre? [Online]. Construction Engineers Australia. Available: https://www.cea-eng.com.au/single-post/2017/12/14/how-much-is-a-cubic-metre [Accessed].

Engage Victoria. 2022. Dublin Road, Ringwood East level crossing removal [Online]. Available: https://engage.vic.gov.au/lxrp-dublin-road [Accessed].

Fang, W., Ding, L., Zhong, B., Love, P. E., & Luo, H. (2018). Automated detection of workers and heavy equipment on construction sites: A convolutional neural network approach. Advanced Engineering Informatics, 37, 139–149.

Géron, A. (2022). Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow. O'Reilly Media, Inc.

Golparvar-Fard, M., Heydarian, A., & Niebles, J. C. (2013). Vision-based action recognition of earthmoving equipment using spatio-temporal features and support vector machine classifiers. Advanced Engineering Informatics, 27(4), 652–663.

Gong, J., Caldas, C. H., & Gordon, C. (2011). Learning and classifying actions of construction workers and equipment using Bag-of-Video-Feature-Words and Bayesian network models. Advanced Engineering Informatics, 25(4), 771–782.

Hikvision DS-2CD2387G2-L(U) 8 MP ColorVu Fixed Turret Network Camera.

Hikvision iDS-2CD8A86G0-XZ(H)S(Y) 8 MP DeepinView Multi-sensor Bullet Camera.

Hive Research & Development 2023. LXRP Productivity & Benchmarking Objectives: Elevating construction project efficiency and productivity through transformative visual insights.

Hive Research & Development 2024b. Visualisation Dashboard.

Hive Research & Development. 2024a. LXRP Productivity & Benchmarking Objectives [Online]. Confluence. Available: https://levelcrossings.atlassian.net/wiki/spaces/HRT/pages/2009235532/LXRP+Productivity+Benchmarking+Objectives [Accessed].

Kim, H., Bang, S., Jeong, H., Ham, Y., & Kim, H. (2018). Analyzing context and productivity of tunnel earthmoving processes using imaging and simulation. Automation in Construction, 92, 188–198. https://doi.org/10.1016/j.autcon.2018.04.002

Kim, H., Ham, Y., Kim, W., Park, S., & Kim, H. (2019). Vision-based nonintrusive context documentation for earthmoving productivity simulation. Automation in Construction, 102, 135–147. https://doi.org/10.1016/j.autcon.2019.02.006

Kim, H., Kim, H., Hong, Y. W., & Byun, H. (2018). Detecting construction equipment using a region-based fully convolutional network and transfer learning. Journal of Computing in Civil Engineering, 32(2), 04017082.

Kim, H., Kim, K., & Kim, H. (2016). Vision-Based Object-Centric Safety Assessment Using Fuzzy Inference: Monitoring Struck-By Accidents with Moving Objects. Journal of Computing in Civil Engineering, 30(4), 04015075. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000562

Kim, J., & Chi, S. (2017). Adaptive detector and tracker on construction sites using functional integration and online learning. Journal of Computing in Civil Engineering, 31(5), 04017026.

Kim, J., & Chi, S. (2019). Action recognition of earthmoving excavators based on sequential pattern analysis of visual features and operation cycles. Automation in Construction, 104, 255–264.

Kim, J., & Chi, S. (2020). Multi-camera vision-based productivity monitoring of earthmoving operations. Automation in Construction, 112, 103121. https://doi.org/10.1016/j.autcon.2020.103121

Kim, J., Chi, S., & Seo, J. (2018). Interaction analysis for vision-based activity identification of earthmoving excavators and dump trucks. Automation in Construction, 87, 297–308.

Kim, J., Hwang, J., Chi, S., & Seo, J. (2020). Towards database-free vision-based monitoring on construction sites: A deep active learning approach. Automation in Construction, 120, 103376. https://doi.org/10.1016/j.autcon.2020.103376

Kim, K., Kim, H., & Kim, H. (2017). Image-based construction hazard avoidance system using augmented reality in wearable device. Automation in Construction, 83, 390–403. https://doi.org/10.1016/j.autcon.2017.06.014

Level Crossing Removal 2022. Productivity Benchmarking Procedure.

Level Crossing Removal 2023. LX Benchmarking Template Earthworks in Cut_December 23.

Level Crossing Removal 2024. AB_DRAFT_SEPA_Dublin_Earthworks_Cut_Data_13042024.

Mckinsey Global Institute 2017. Reinventing Construction: A Route to Higher Productivity.

Memarzadeh, M., Golparvar-Fard, M., & Niebles, J. C. (2013). Automated 2D detection of construction equipment and workers from site video streams using histograms of oriented gradients and colors. Automation in Construction, 32, 24–37. https://doi.org/10.1016/j.autcon.2012.12.002

Pricewaterhousecoopers Consulting (Australia) Pty Ltd 2019. Transforming Australian manufacturing: Preparing businesses and workplaces for Industry 4.0. Swinburne University of Technology.

Rezazadeh Azar, E. (2017). Semantic annotation of videos from equipment-intensive construction operations by shot recognition and probabilistic reasoning. Journal of Computing in Civil Engineering, 31(5), 04017042.

Rezazadeh Azar, E., & McCabe, B. (2012a). Automated Visual Recognition of Dump Trucks in Construction Videos. Journal of Computing in Civil Engineering, 26(6), 769–781. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000179

Rezazadeh Azar, E., & McCabe, B. (2012b). Part based model and spatial–temporal reasoning to recognize hydraulic excavators in construction images and videos. Automation in Construction, 24, 194–202. https://doi.org/10.1016/j.autcon.2012.03.003

Rezazadeh Azar, E., Dickinson, S., & McCabe, B. (2013). Server-Customer Interaction Tracker: Computer Vision–Based System to Estimate Dirt-Loading Cycles. Journal of Construction Engineering and Management, 139(7), 785–794. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000652

Roberts, D., & Golparvar-Fard, M. (2019). End-to-end vision-based detection, tracking and activity analysis of earthmoving equipment filmed at ground level. Automation in Construction, 105, 102811.

Tajeen, H., & Zhu, Z. (2014). Image dataset development for measuring construction equipment recognition performance. Automation in Construction, 48, 1–10.

Victoria's Big Build. 2022. Designs revealed for the Dublin Road level crossing removal [Online]. Available: https://bigbuild.vic.gov.au/news/level-crossing-removal-project/designs-revealed-for-the-dublin-road-level-crossing-removal [Accessed].

weigh-more solutions. Model AWS106 / AWS108 Concrete Weighbridges [Online]. Available: https://www.weigh-more.com.au/concrete-weighbridges/ [Accessed]

Zou, J., & Kim, H. (2007). Using Hue, Saturation, and Value Color Space for Hydraulic Excavator Idle Time Analysis. Journal of Computing in Civil Engineering, 21(4), 238–246. https://doi.org/10.1061/(ASCE)0887-3801(2007)21:4(238)

APPENDICES

Appendix A – LXRP Tracking Spreadsheet Example

Activity	UoM	Work Dor	Crew	Description	DescriptionTyp	Qty	Work Zor
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	h	9.25	Crew 1	Excavator	Plant	1	Zone 2
Primary Load-Out Excavator (LOE)	h	9.25	Crew 1	Excavator	Plant	1	Zone 2
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	h	9.25	Crew 1	Excavator	Plant	1	Zone 2
Tandem	Bm3	212.5	Crew 1	Tandem	Plant	1	Zone 2
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	h	5.55	Crew 2	Dozer	Plant	1	Zone 4
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	h	3.7	Crew 2	Dozer	Plant	1	Zone 5
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	h	5.55	Crew 2	Excavator	Plant	1	Zone 4
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	h	3.7	Crew 2	Excavator	Plant	1	Zone 5
Primary Load-Out Excavator (LOE)	h	7.75	Crew 1	Excavator	Plant	1	Zone 2
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	h	7.75	Crew 1	Excavator	Plant	1	Zone 2
Tandem	Bm3	331.25	Crew 1	Tandem	Plant	1	Zone 2
Primary Load-Out Excavator (LOE)	h	4.65	Crew 2	Excavator	Plant	1	Zone 4
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	h	4.65	Crew 2	Dozer	Plant	1	Zone 4
Haulage Truck & Trailers	Bm3	225	Crew 2	Truck & Trailer	Plant	1	Zone 4
Primary Load-Out Excavator (LOE)	h	3.1	Crew 2	Excavator	Plant	1	Zone 5
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	h	3.1	Crew 2	Dozer	Plant	1	Zone 5
Haulage Truck & Trailers	Bm3	150	Crew 2	Truck & Trailer	Plant	1	Zone 5

Activity	Materi	Bench	Start Date Time	Finish Date Time	Hours	Delay1
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	OTR	1	10/01/2024 07:00	10/01/2024 17:00	10	0.5
Primary Load-Out Excavator (LOE)	OTR	1	11/01/2024 07:00	11/01/2024 17:00	10	
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	OTR	1	11/01/2024 07:00	11/01/2024 17:00	10	
Tandem	OTR	1	11/01/2024 07:00	11/01/2024 17:00	10	
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	OTR	1	11/01/2024 07:00	11/01/2024 17:00	10	
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	OTR	1	11/01/2024 07:00	11/01/2024 17:00	10	
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	OTR	1	11/01/2024 07:00	11/01/2024 17:00	10	
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	OTR	1	11/01/2024 07:00	11/01/2024 17:00	10	
Primary Load-Out Excavator (LOE)	OTR	1	12/01/2024 07:00	12/01/2024 15:30	8.5	
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	OTR	1	12/01/2024 07:00	12/01/2024 15:30	8.5	
Tandem	OTR	1	12/01/2024 07:00	12/01/2024 15:30	8.5	
Primary Load-Out Excavator (LOE)	OTR	1	12/01/2024 07:00	12/01/2024 15:30	8.5	
Secondary Plant supporting LOE (Ripping, dozing, loading, hauling, dumping, stockpiling within the cut)	OTR	1	12/01/2024 07:00	12/01/2024 15:30	8.5	
Haulage Truck & Trailers	OTR	1	12/01/2024 07:00	12/01/2024 15:30	8.5	
Primary Load-Out Excavator (LOE)	OTR	1	12/01/2024 07:00	12/01/2024 15:30	8.5	

Appendix B – Camera Installation and Configuration Guidelines

Table 28. Hikvision camera specifications (2024)

HIKVISION

▪ Specification

Camera	
Image Sensor	1/1.2" Progressive Scan CMOS
Max. Resolution	3840 × 2160
Min. Illumination	Color： 0.0005 Lux @ (F1.0, AGC ON)
Shutter Speed	1/3 s to 1/100,000 s
Day & Night	24/7 Color imaging
Angle Adjustment	Pan: 0° to 360°, tilt: 0° to 75°, rotate: 0° to 360°
Lens	
Lens Type	Fixed focal lens, 2.8 and 4 mm optional
Focal Length & FOV	2.8 mm, horizontal FOV 102°, vertical FOV 52°, diagonal FOV 124° 4 mm, horizontal FOV 88°, vertical FOV 47°, diagonal FOV 104°
Lens Mount	M16
Iris Type	Fixed
Aperture	F1.0
Depth of Field	2.8 mm: 3.1 m to ∞ 4 mm: 3.6 m to ∞
DORI	
DORI	2.8 mm: D: 96 m, O: 38 m, R: 19 m, I: 9 m 4 mm: D: 102 m, O: 40 m, R: 20 m, I: 10 m
Illuminator	
Supplement Light Type	White Light
Supplement Light Range	Up to 30 m
Smart Supplement Light	Yes
Video	
Main Stream	50 Hz: 25 fps (3840 × 2160, 3200 × 1800 , 2688 × 1520, 1920 × 1080, 1280 × 720) 60 Hz: 24 fps (3840 × 2160) 30 fps (3200 × 1800 , 2688 × 1520, 1920 × 1080, 1280 × 720)
Sub-Stream	50 Hz: 25 fps (640 × 480, 640 × 360) 60 Hz: 30 fps (640 × 480, 640 × 360)
Third Stream	50 Hz: 10 fps (1920 × 1080, 1280 × 720, 640 × 480, 640 × 360) 60 Hz: 10 fps (1920 x 1080, 1280 × 720, 640 × 480, 640 × 360)
Video Compression	Main stream: H.265/H.264/H.264+/H.265+ Sub-stream: H.265/H.264/MJPEG Third stream: H.265/H.264
Video Bit Rate	32 Kbps to 16 Mbps
H.264 Type	Baseline Profile/Main Profile/High Profile
H.265 Type	Main Profile
Bit Rate Control	CBR/VBR
Scalable Video Coding (SVC)	H.264 and H.265 encoding
Region of Interest (ROI)	1 fixed region for main stream and sub-stream
Audio	
Environment Noise Filtering	-U: Yes

Table 29. Video data collection summary of considerations

Stage	Process	Description
Data Collection	**Camera Setup**	Installation of cameras strategically around the site to cover all necessary angles for earthwork monitoring.
	Video Capture	Continuous or interval-based capturing of video during earthwork operations, with optimal resolution and frame rate
	Data Transmission	Transferring the captured video data to a processing site remotely (cloud).
Data Processing	**Data Processing**	Enhancing video quality through stabilisation and resolution enhancement
	Object Detection and Tracking	Using computer vision algorithms to identify and track objects such as equipment and personnel involved in earthwork.
	Feature Extraction	Extracting relevant features from the video, such as equipment operation times, movement patterns, and volumes moved.
	Data Interpretation	Analysing extracted features to derive actionable insights for optimising earthwork operations.
Data Storage and Management	**Storage**	Efficiently storing processed data in a way that optimises space and maintains accessibility.
	Data Management	Organising, maintaining, and securing video data, ensuring integrity and compliance with data protection laws.

Stage	Process	Description
Privacy and Compliance	**Privacy Protection**	Ensuring the video data collection complies with privacy laws and regulations.
	Data Anonymisation	Masking or anonymising identifiable information to protect privacy
	Legal Compliance	Adhering to legal standards and obtaining necessary permissions.
System Reliability	**Hardware Reliability**	Ensuring cameras and other equipment function properly without failures
	Network Reliability	Maintaining a robust network for uninterrupted data transmission.
	Backup Systems	Implementing backup systems to prevent data loss in case of failures.
Data Security	**Encryption**	Encrypting video data during transmission and storage for security.
	Access Control	Restricting access to the video data to authorised personnel only.
Quality Assurance	**Data Quality Checks**	Regularly verifying the quality and accuracy of the collected data.
	System Audits	Conducting periodic audits to ensure the system is functioning as intended.
Scalability	**Scalability**	Ensuring the system can handle increasing amounts of data as the project grows.
	Futureproofing	Planning for future technological upgrades and expansions.
Environmental Conditions	**Weather Monitoring**	Adjusting data collection methods based on weather conditions.
	Site Lighting	Ensuring adequate lighting for clear video capture during all times of day.

Table 30. Camera Types and Specifications

Feature	Recommendation
Camera Types	Use a combination of Dome and Bullet cameras for general coverage, and PTZ cameras for wide area coverage
Resolution	Minimum 1080p for clear footage; higher resolution for detailed area monitoring
Weatherproof and Dust-proof	Cameras must be robust to withstand environmental challenges (rain, dust, temperature changes)
Night Vision	Ensure cameras have night vision capabilities for monitoring low-light conditions
Additional Features	Pan, Tilt, Zoom (PTZ) capabilities, motion detection, remote access

Table 31. Placement Strategy (more specific in range of the camera – FOV, viewing angle)

Criteria	Recommendation
General Placement	High vantage points for comprehensive coverage. To capture to the truck loadout needs minimum of how far away
Excavation Areas	Place cameras to monitor excavation activities, ensuring clear views of digging and earth movement (bucket swing)
Truck Loading Zones	Monitor areas where trucks are loaded with excavated material
Entry and Exit Points	Monitor all entry and exit points to track vehicle movement (license plate). LPR camera
Rail Over (a bridge)/ Under the Trench	Place cameras above and below trench rail passes to monitor structural integrity and work progress. Ensure clear views of any potential hazards. (mounting the wall with cage, how to protect the camera from people). Example camera positioning (project have done that). Recommendation: Additional camera (entry and exit point)

Table 32. Number of Cameras

Criteria	Recommendation
Site Size and Complexity	Higher resolution for longer range surveillance; PTZ cameras for extensive coverage areas (recommended camera in entry and exit point, loadout area. 2 cameras in camera pole) (example: LPO camera)
Coverage Gaps	Ensure no blind spots in coverage

Table 33. Range, Camera Type, and Resolution

Feature	Recommendation
Range and Type Compatibility	Determine the number of cameras based on the size and complexity of the site
Environmental Considerations	Weatherproof and durable cameras for outdoor settings
Motion Detection and PTZ	PTZ cameras for dynamic monitoring; motion detection for efficiency.

Table 34. Installation and Power Supply

Criteria	Recommendation
Mounting Heights and Angles	Optimise mounting heights and angles for maximum coverage and minimum tampering
Power Supply	Use reliable power sources; solar power with batteries are most appropriate for the transient nature of construction sites.

Table 35. Monitoring

Criteria	Recommendation
Real-Time Monitoring	Implement real-time monitoring

Table 36. Legal and Privacy Compliance

Criteria	Recommendation
Compliance with Local Laws	Follow local regulations regarding video surveillance
Signage	Place sufficient signage to inform personnel and visitors of surveillance (QR-code)
Privacy	Set up privacy zones digitally or physically to avoid recording sensitive areas. Use software to blur individuals captured in video footage to ensure privacy

Appendix C – Selected Time Windows

TABLE LEGEND

- **CAM4** footage is available.
- No excavation and haulage activity occurred on **CAM4**.
- **CAM4** footage is available and plenty of excavation and haulage activity occurred on camera's FOV.

TIME WINDOW TABLE

Camera No	Date	Total Loads (Load Sheet)	Footage Available? (Kinesis)	Footage Exported? (labelled)	Labelled (status)	Status/Comment
CAM4	1 Feb 2024	94	NO	✗	✗	No footage is available on Kinesis for this date
CAM4	2 Feb 2024	45	NO	✗	✗	Footage is only available on Kinesis from 14:21 onwards
CAM4	8 Feb 2024	65	YES	NO	NO	
CAM4	9 Feb 2024	146	YES	NO	NO	
CAM4	13 Feb 2024	0	YES	YES	✗	No excavation & haulage activity at the camera fov
CAM4	14 Feb 2024	0	YES	YES	✗	No excavation & haulage activity at the camera fov
CAM4	15 Feb 2024	103	YES	YES	ONGOING	video files show more than 17 loads, perhaps some load sheets are missing.
CAM4	16 Feb 2024	145	YES	YES	ONGOING	
CAM4	17 Feb 2024	60	NO	✗	✗	No footage is available on Kinesis for this date
CAM4	28 Feb 2024	131	YES	NO	NO	
CAM4	29 Feb 2024	204	YES	NO	NO	
CAM4	14 Mar 2024	0	YES	NO	✗	No excavation & haulage activity at the camera fov
CAM4	15 Mar 2024	169	YES	NO	NO	
CAM4	16 Mar 2024	147	NO	✗	✗	No footage is available on Kinesis for this date
CAM4	18 Mar 2024	89	YES	NO	NO	
CAM4	19 Mar 2024	0	YES	NO	✗	No excavation & haulage activity at the camera fov
CAM4	20 Mar 2024	0	YES	NO	✗	No excavation & haulage activity at the camera fov

Figure 65. Time Window for excavation and haulage activity

The **Time Window Table** provides a structured overview of footage availability, excavation activity, and haulage operations, specifically focusing on **Camera 4 (CAM4)**. Each row in the table corresponds to a specific date, summarising key details such as the total number of loads recorded from load sheets, the availability of footage on **Amazon Kinesis**, and the status of footage labelling.

Key Elements of the Table:

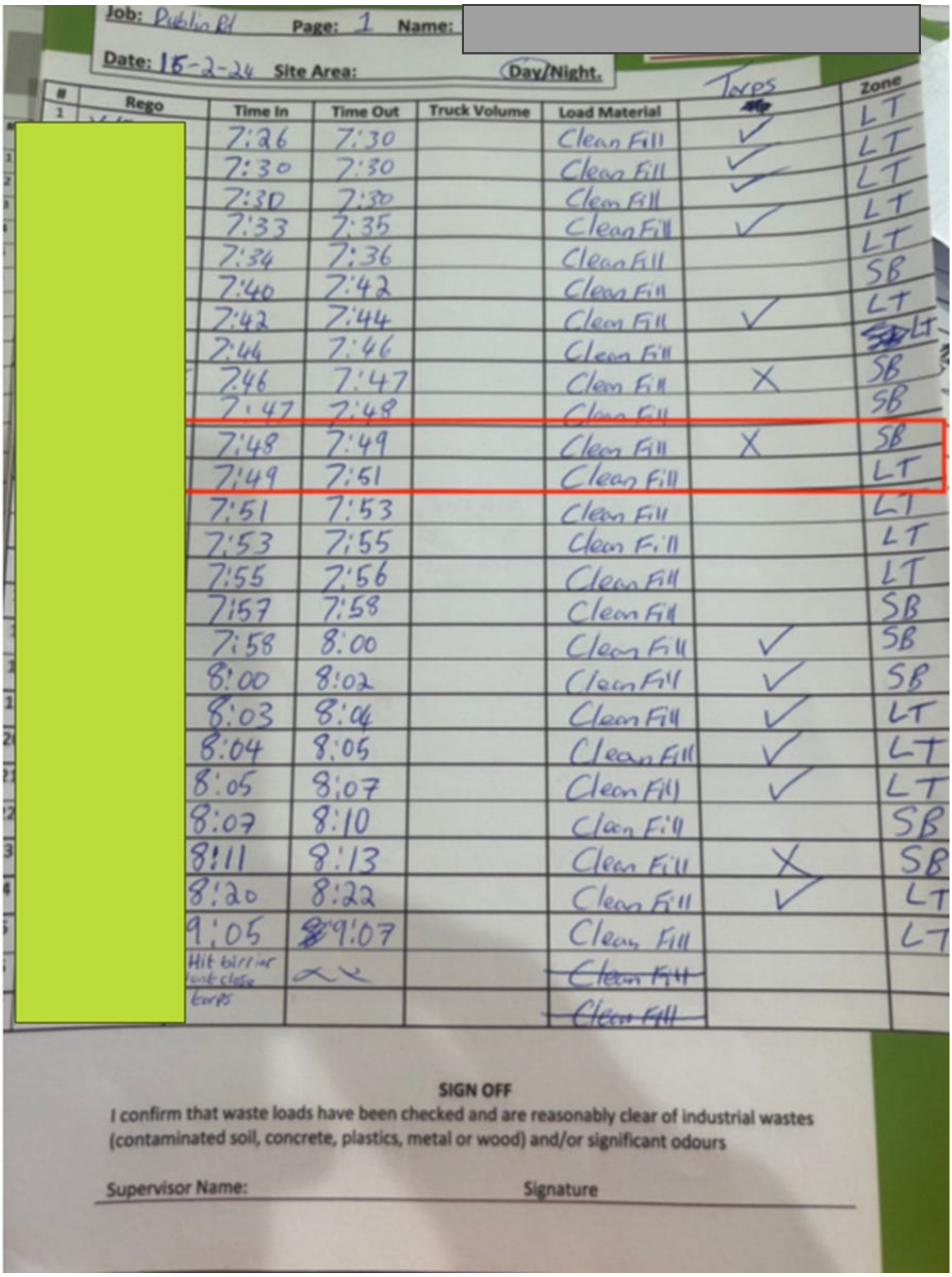
1. **Footage Availability**:
   - The table uses colour codes to indicate whether footage is available for each date:
     - **Green** indicates that footage is available and includes substantial excavation and haulage activity within the camera's field of view (FOV).
     - **Yellow** represents dates where no significant excavation or haulage activity occurred despite the availability of load sheets.
     - **Red** marks dates where footage is unavailable for verification.
2. **Total Loads (from Load Sheets)**:
   - The table records the number of haulage truck loads based on load sheets, which helps correlate operational data with available footage. Dates with high truck counts (e.g.,**16 Feb**, with 145 loads) are marked in **green**, indicating these days are important for verification.
3. **Footage Exported and Labelling Status**:
   - These columns track the status of footage export and labelling for each date. Dates where footage has been exported and is under review for labelling are marked with **ongoing** statuses, ensuring the team is aware of progress.
   - Some dates (marked with **red or yellow**) indicate no footage or load sheet was available, thus limiting the ability to manually label and validate those periods.

Validation Metrics for Selected Time Windows

During the selected time windows, the following metrics will be extracted and compared with AI-generated data:

- **Count of People**: Manual counting of workers detected in the camera's FOV during the selected periods.
- **Count of Plant**: Verification of the AI's detection of different types of equipment (excavators, trucks, etc.).
- **Utilisation Rate of Plant**: Comparison of AI-generated plant utilisation rates with manually recorded data.
- **Count of Buckets Unloaded to Trucks**: Manual counting of the number of times excavators load spoil into trucks, validated against AI data.

Appendix D – Manual recording of haulage operation



Job: Public Rd   Page: 1   Name:

Date: 15-2-24   Site Area: Day/Night.

#	Rego	Time In	Time Out	Truck Volume	Load Material	Tarps	Zone
1		7:26	7:30		Clean Fill	✓	LT
		7:30	7:30		Clean Fill	✓	LT
		7:30	7:30		Clean Fill	✓	LT
		7:33	7:35		Clean Fill	✓	LT
		7:34	7:36		Clean Fill		LT
		7:40	7:42		Clean Fill		SB
		7:42	7:44		Clean Fill	✓	LT
		7:44	7:46		Clean Fill		~~SB~~ LT
		7:46	7:47		Clean Fill	X	SB
		7:47	7:48		Clean Fill		SB
		7:48	7:49		Clean Fill	X	SB
		7:49	7:51		Clean Fill		LT
		7:51	7:53		Clean Fill		LT
		7:53	7:55		Clean Fill		LT
		7:55	7:56		Clean Fill		LT
		7:57	7:58		Clean Fill		SB
		7:58	8:00		Clean Fill	✓	SB
		8:00	8:02		Clean Fill	✓	SB
		8:03	8:04		Clean Fill	✓	LT
		8:04	8:05		Clean Fill	✓	LT
		8:05	8:07		Clean Fill	✓	LT
		8:07	8:10		Clean Fill		SB
		8:11	8:13		Clean Fill	X	SB
		8:20	8:22		Clean Fill	✓	LT
		9:05	~~8~~9:07		Clean Fill		LT
		Hit barrier [illegible]			~~Clean Fill~~		
		[illegible]			~~Clean Fill~~		

SIGN OFF

I confirm that waste loads have been checked and are reasonably clear of industrial wastes (contaminated soil, concrete, plastics, metal or wood) and/or significant odours

Supervisor Name: Signature

Figure 66. Truck count site sheet – CAM 4

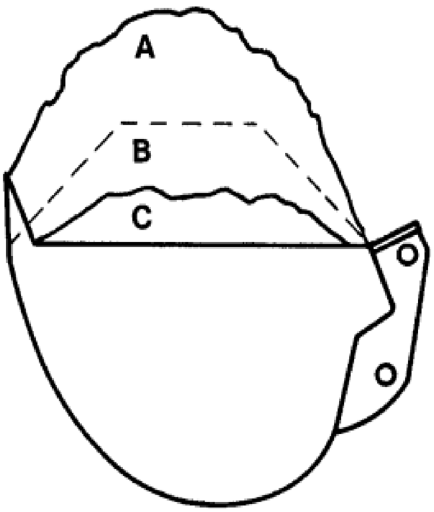
Appendix E – Bucket Payload

BUCKET PAYLOAD

An excavator's bucket payload (actual amount of material in the bucket on each digging cycle) is dependent on bucket size, shape, curl force, and certain soil characteristics, i.e., the fill factor for that soil. Fill factors for several types of material are listed below.

Average Bucket Payload =
(Heaped Bucket Capacity) × (Bucket Fill Factor)

Material	Fill Factor Range (Percent of heaped bucket capacity)
Moist Loam or Sandy Clay	A — 100-110%
Sand and Gravel	B — 95-110%
Hard, Tough Clay	C — 80-90%
Rock — Well Blasted	60-75%
Rock — Poorly Blasted	40-50%



Working Weights — Bucket & Payload

The following tables give maximum "bucket plus payload" weights to assist in selecting the correct bucket for a specific application. These weights are based on actual job conditions. In better than average conditions the excavator may be able to achieve rated lift capacities listed in this section.

NOTE: Bucket sizes are suitable for a maximum material density of 1800 kg/m³ (3035 lb/yd³). Payloads shown are calculated at 1500 kg/m³ (2530 lb/yd³).

Model	Stick Length mm	Stick Length ft	kg	lb
307B	1665	5'6"	1050	2310
	2210	7'3"	860	1900
307B SB	1665	5'6"	1030	2270
	2210	7'3"	750	1650
307	1665	5'6"	1090	2400
	2210	7'3"	880	1940
311B	1950	6'5"	1560	3440
	2250	7'5"	1470	3240
	2800	9'2"	1230	2710
312B	2100	6'11"	1580	3480
	2500	8'2"	1460	3220
	3000	9'10"	1280	2820
312B L	2100	6'11"	1770	3900
	2500	8'2"	1640	3620
	3000	9'10"	1450	3200
312B L*	2100	6'11"	1740	3830
	2500	8'2"	1595	3510
	3000	9'10"	1450	3190
315B	1850	6'1"	2070	4570
	2250	7'5"	1980	4360
	2600	8'6"	1810	4000
	3100	10'2"	1630	3590
315B L	1850	6'1"	2160	4760
	2250	7'5"	2060	4540
	2600	8'6"	1890	4170
	3100	10'2"	1700	3750
318B L	1800	5'11"	2600	5730
	2250	7'5"	2380	5250
	2700	8'10"	2210	4870
	3200	10'6"	1910	4210
318B LN	1800	5'11"	2230	4920
	2250	7'5"	2030	4480
	2700	8'10"	1900	4190
	3200	10'6"	1630	3590
318B L*/ 318B LN*	1800	5'11"	2440	5380
	2250	7'5"	2250	4960
	2700	8'10"	2160	4760
	3200	10'6"	1810	3990

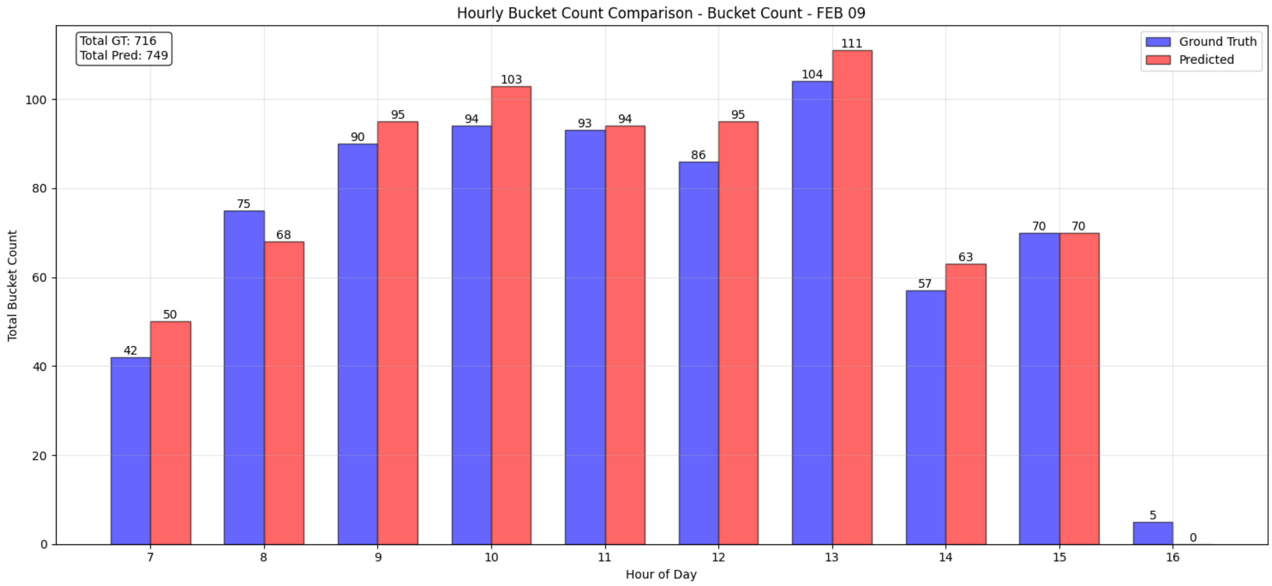
*France sourced.

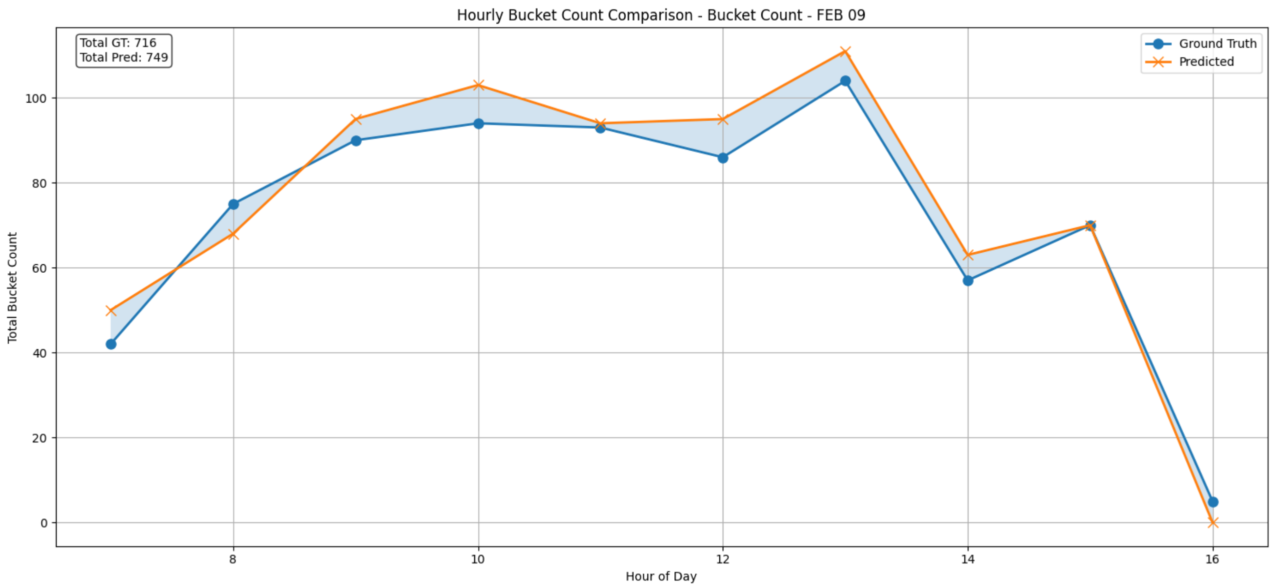
Figure 67. Extract from Caterpillar performance handbook 2019

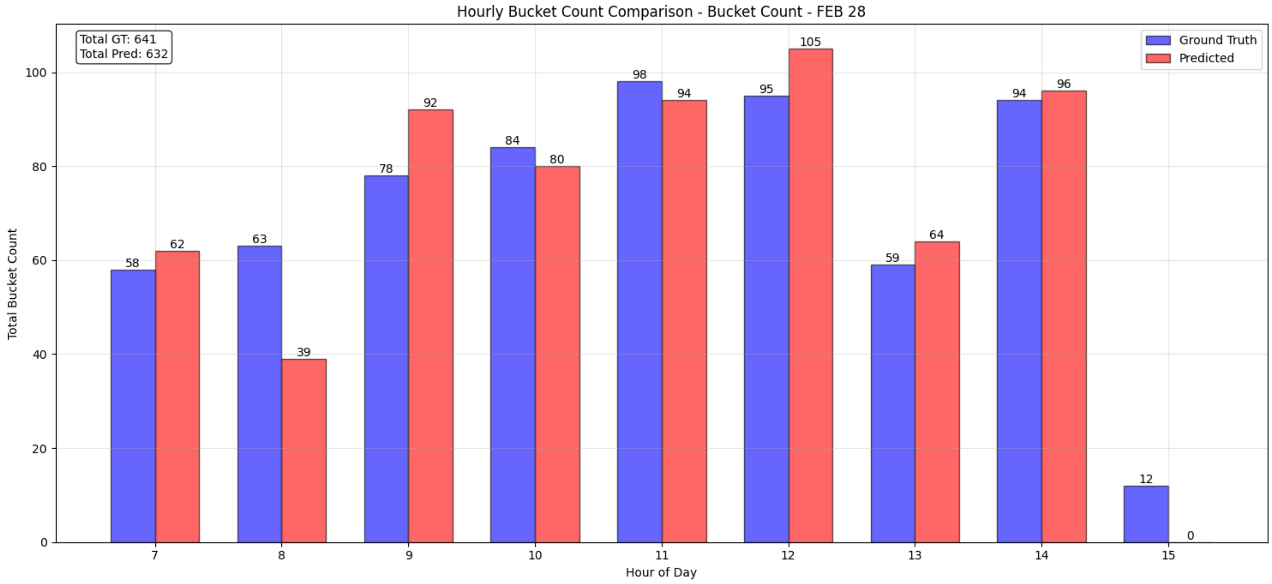
Appendix F – Detailed Comparison of AI-Generated Results

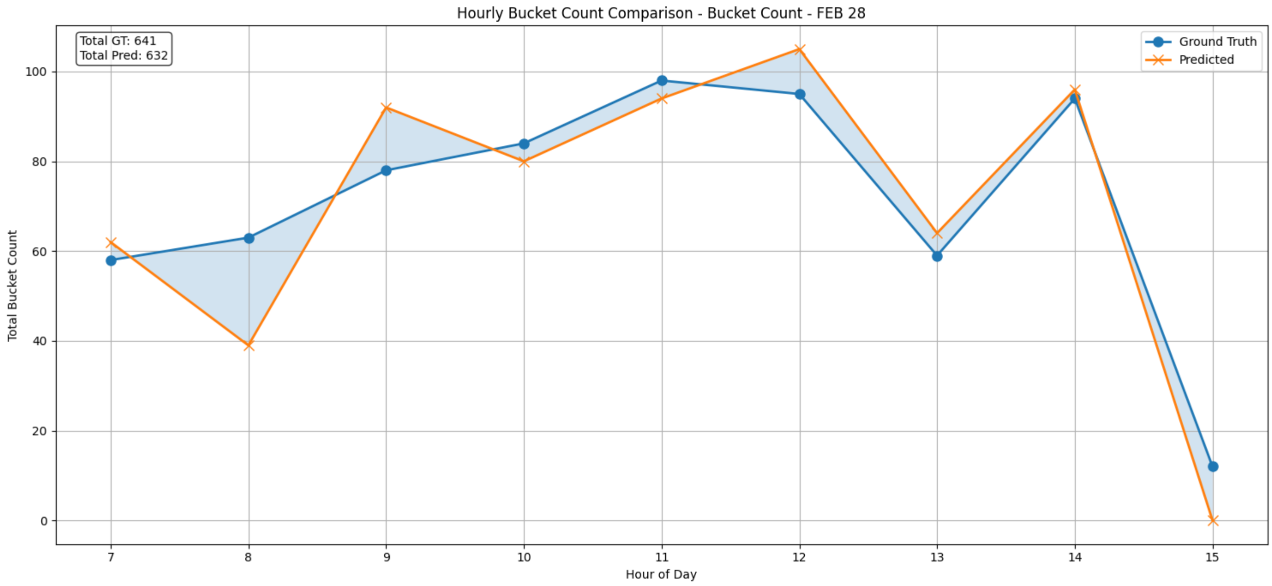
Bucket Count Analysis

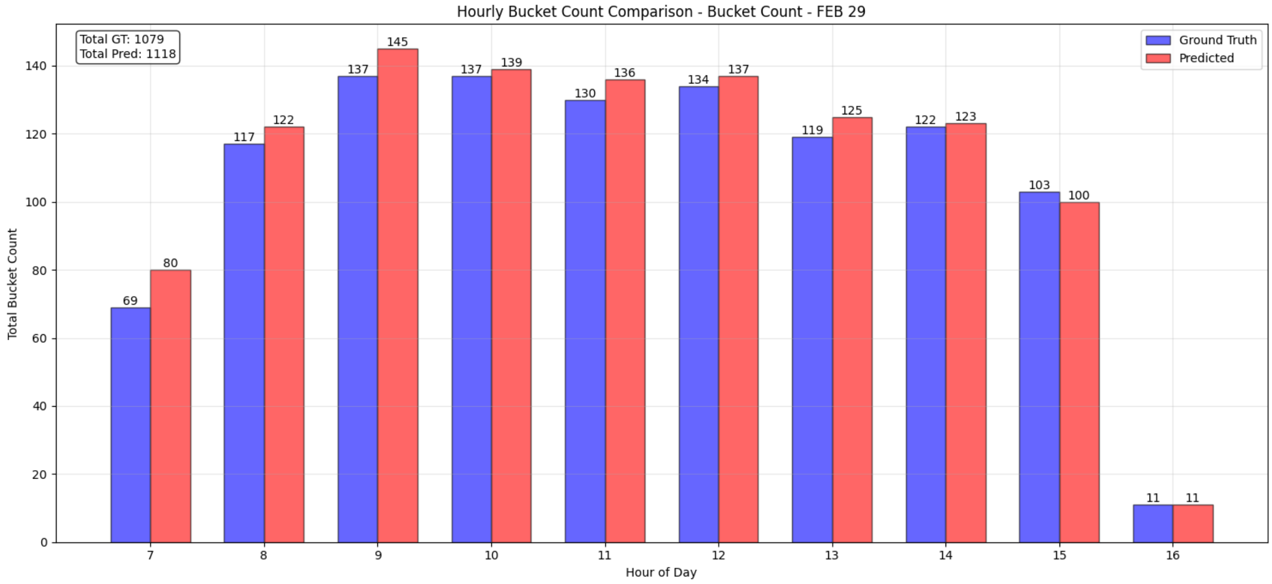
The following four figures show the hourly bucket count comparison between the actual and AI-predicted counts for 9 Feb, 28 Feb, 29 Feb, and 15 Mar, respectively.

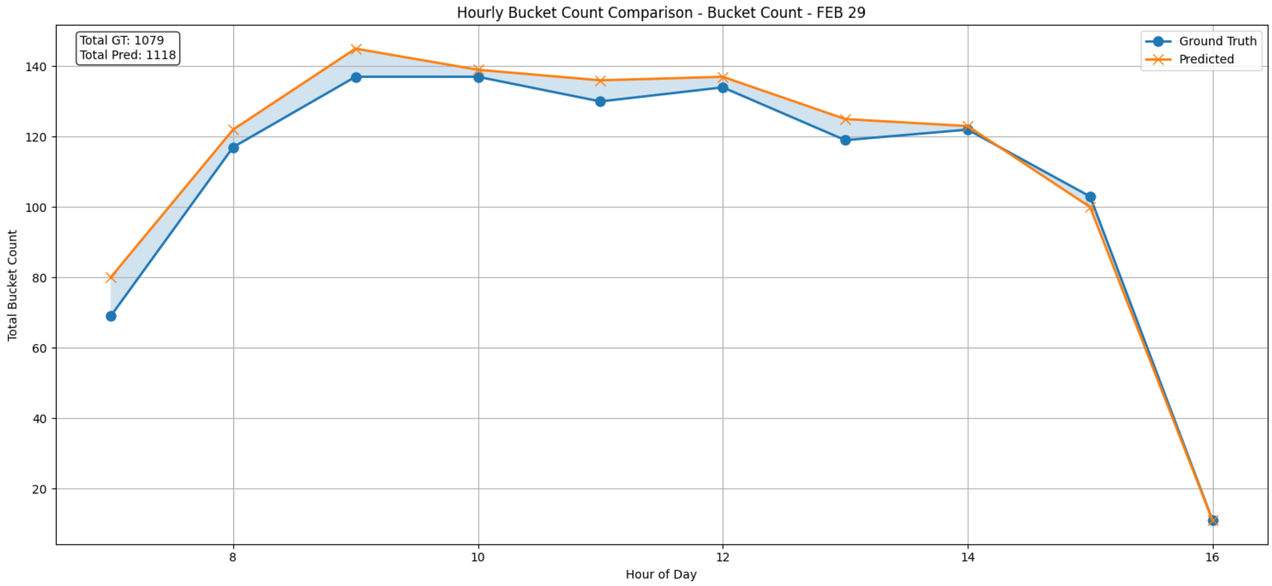


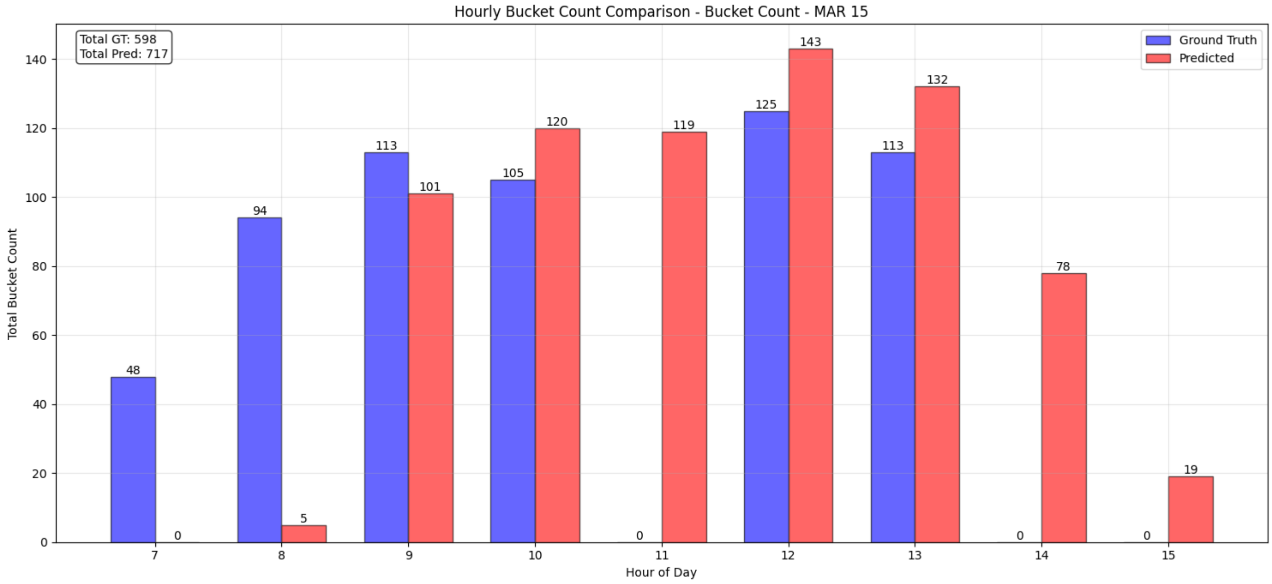


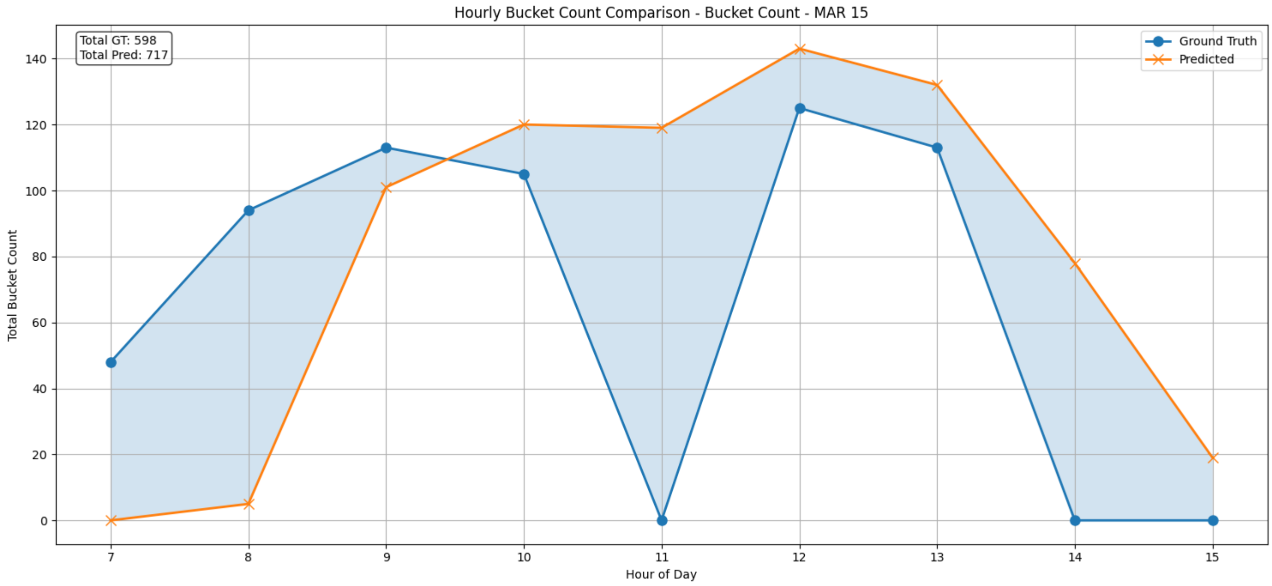

Hourly Bucket Count Comparison - Bucket Count - FEB 28
Total GT: 641
Total Pred: 632
Ground Truth
Predicted
Total Bucket Count
Hour of Day
58
62
63
39
78
92
84
80
98
94
95
105
59
64
94
96
12
0


Hourly Bucket Count Comparison - Bucket Count - FEB 28
Total GT: 641
Total Pred: 632
Ground Truth
Predicted
Total Bucket Count
Hour of Day


Hourly Bucket Count Comparison - Bucket Count - FEB 29
Total GT: 1079
Total Pred: 1118
Ground Truth
Predicted
69
80
117
122
137
145
137
139
130
136
134
137
119
125
122
123
103
100
11
11
Total Bucket Count
Hour of Day


Hourly Bucket Count Comparison - Bucket Count - FEB 29
Total GT: 1079
Total Pred: 1118
Ground Truth
Predicted
Total Bucket Count
Hour of Day

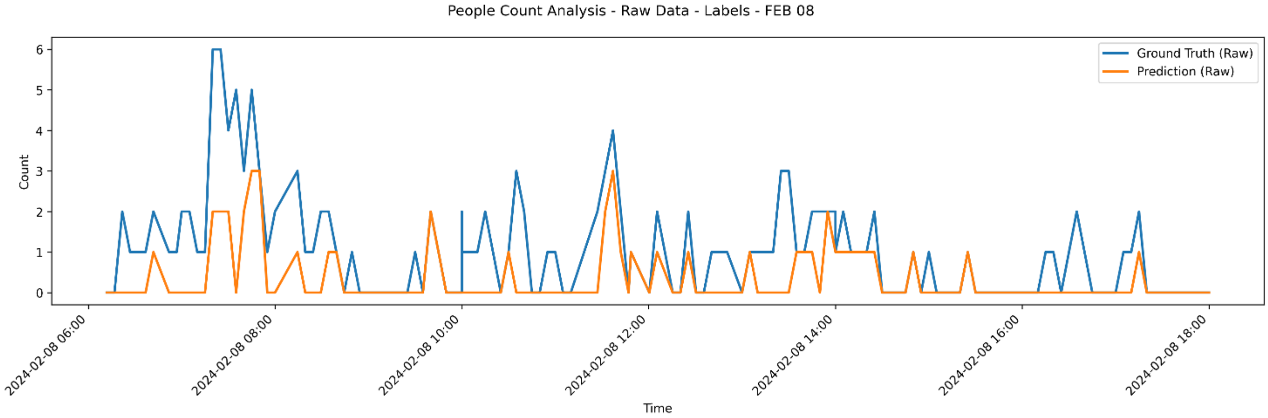

Hourly Bucket Count Comparison - Bucket Count - MAR 15
Total GT: 598
Total Pred: 717
Ground Truth
Predicted
Total Bucket Count
Hour of Day
48
0
94
5
113
101
105
120
0
119
125
143
113
132
0
78
0
19

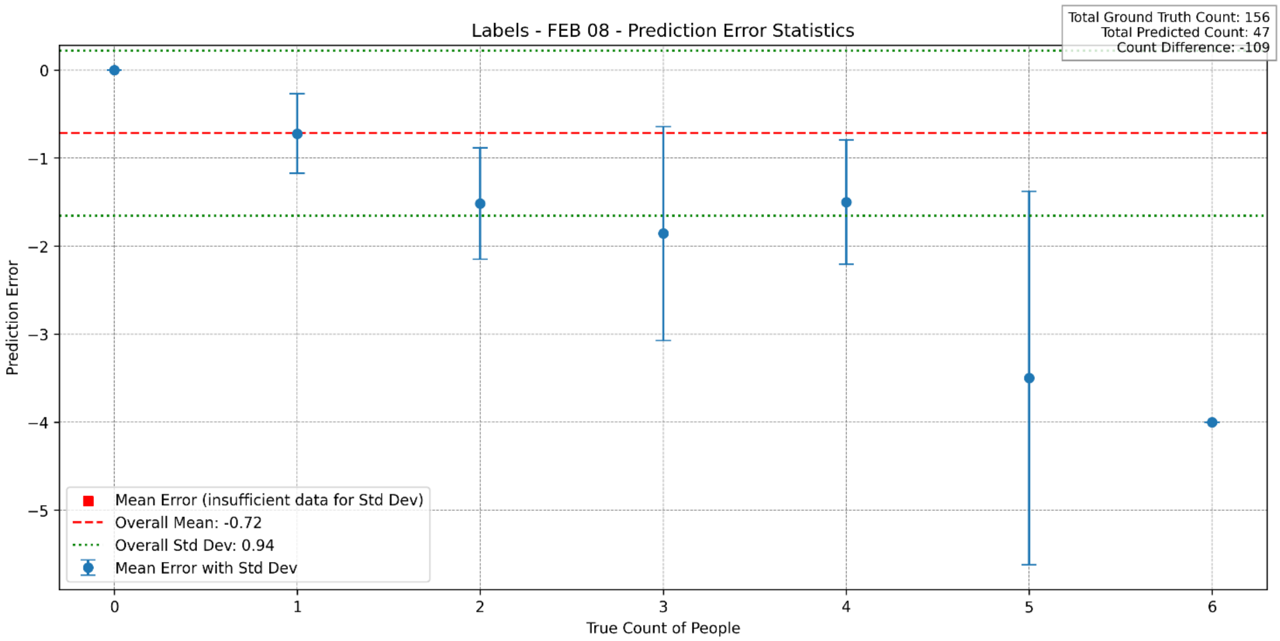

Hourly Bucket Count Comparison - Bucket Count - MAR 15
Total GT: 598
Total Pred: 717
Ground Truth
Predicted
Total Bucket Count
Hour of Day

People Count Analysis

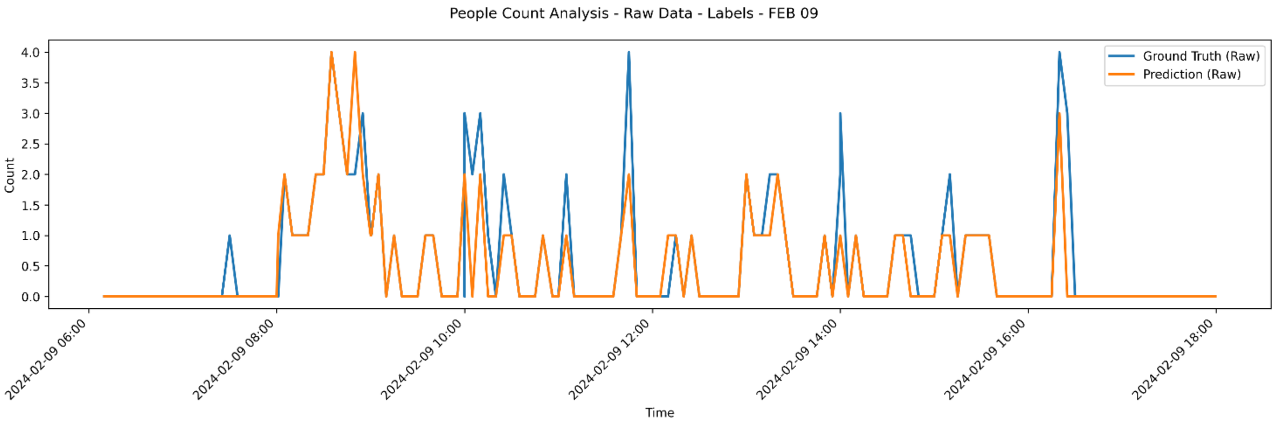
Figures (raw counts and prediction error statistics)

8 Feb 2024

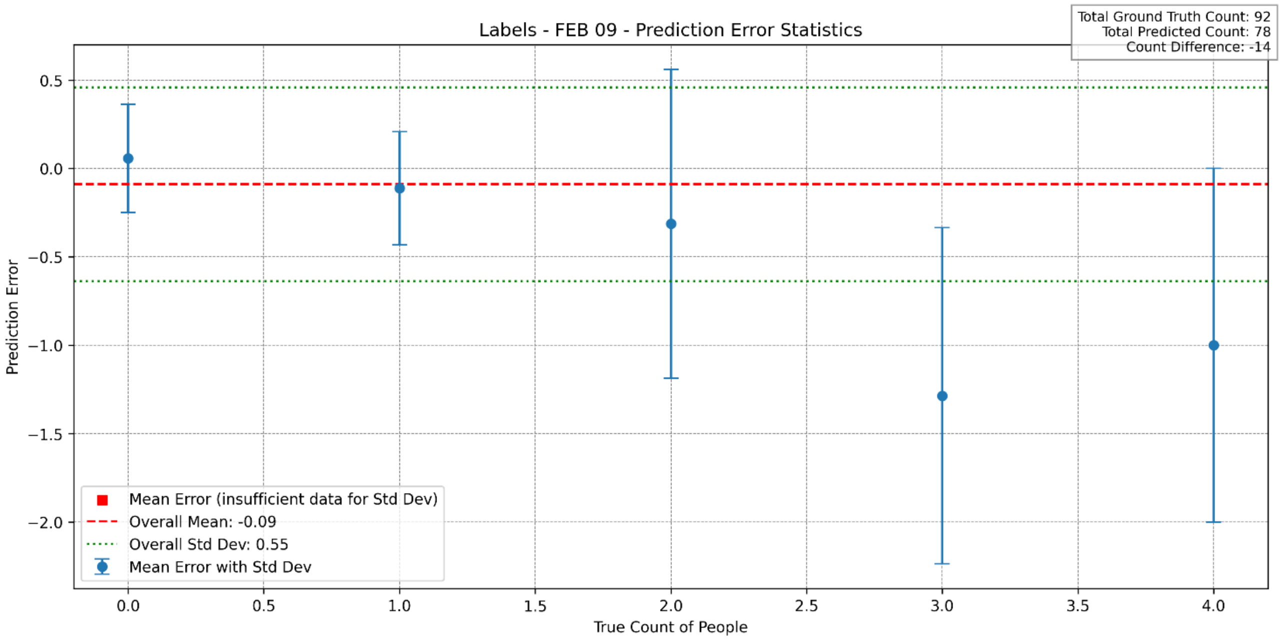




9 Feb 2024

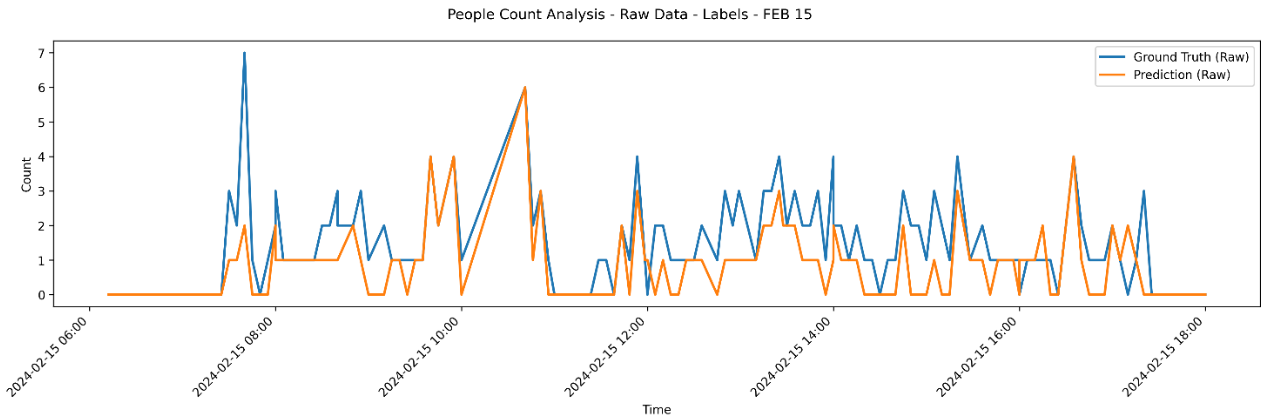


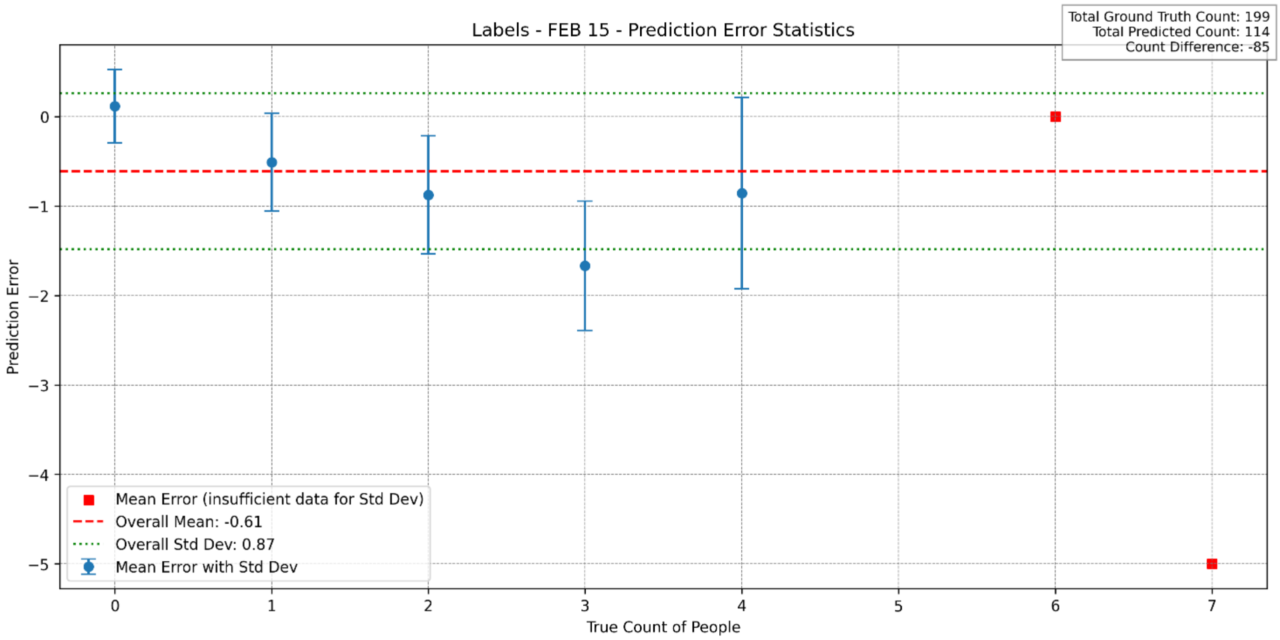
People Count Analysis - Raw Data - Labels - FEB 09
Ground Truth (Raw)
Prediction (Raw)
Count
Time
2024-02-09 06:00
2024-02-09 08:00
2024-02-09 10:00
2024-02-09 12:00
2024-02-09 14:00
2024-02-09 16:00
2024-02-09 18:00



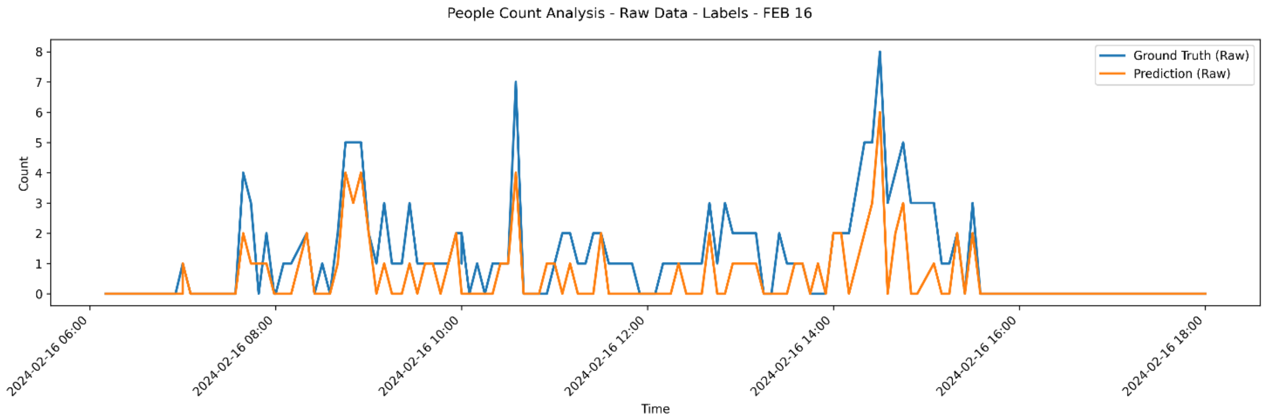
Labels - FEB 09 - Prediction Error Statistics
Total Ground Truth Count: 92
Total Predicted Count: 78
Count Difference: -14
Prediction Error
True Count of People
Mean Error (insufficient data for Std Dev)
Overall Mean: -0.09
Overall Std Dev: 0.55
Mean Error with Std Dev

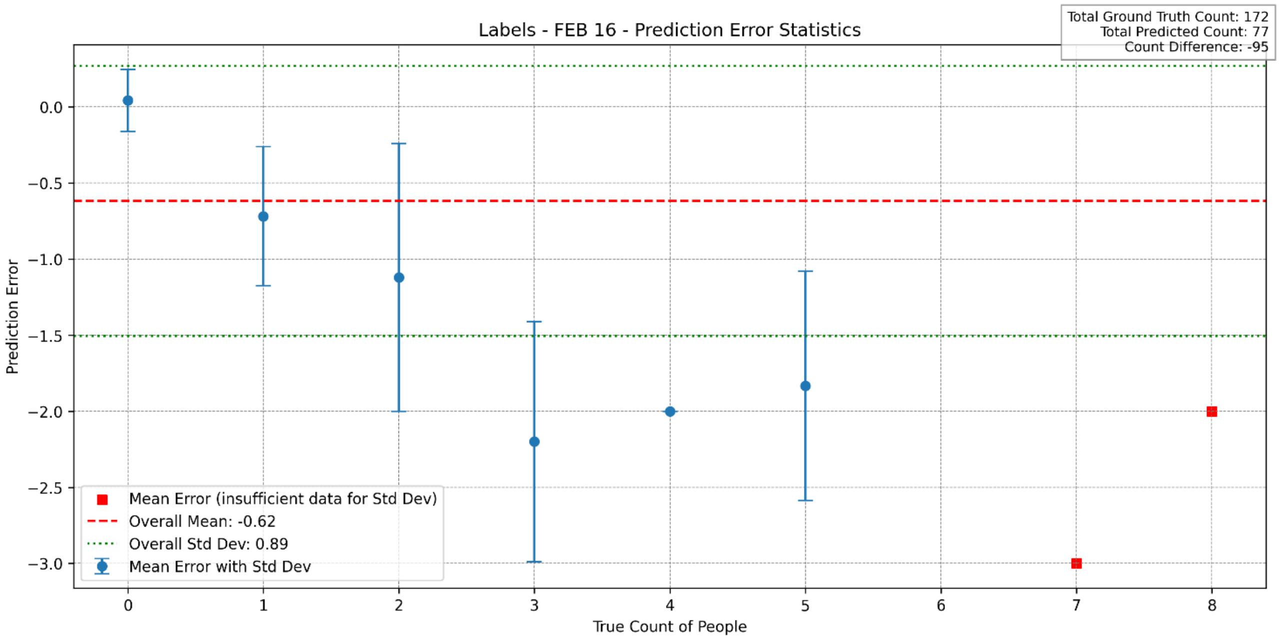
15 Feb 2024


People Count Analysis - Raw Data - Labels - FEB 15
Ground Truth (Raw)
Prediction (Raw)
Count
Time
2024-02-15 06:00
2024-02-15 08:00
2024-02-15 10:00
2024-02-15 12:00
2024-02-15 14:00
2024-02-15 16:00
2024-02-15 18:00

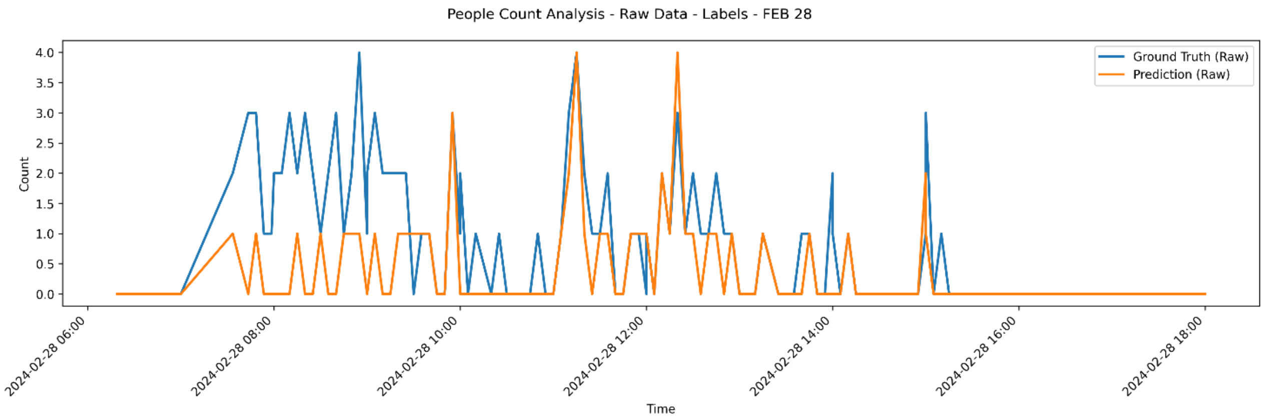

Labels - FEB 15 - Prediction Error Statistics
Total Ground Truth Count: 199
Total Predicted Count: 114
Count Difference: -85
Prediction Error
True Count of People
Mean Error (insufficient data for Std Dev)
Overall Mean: -0.61
Overall Std Dev: 0.87
Mean Error with Std Dev

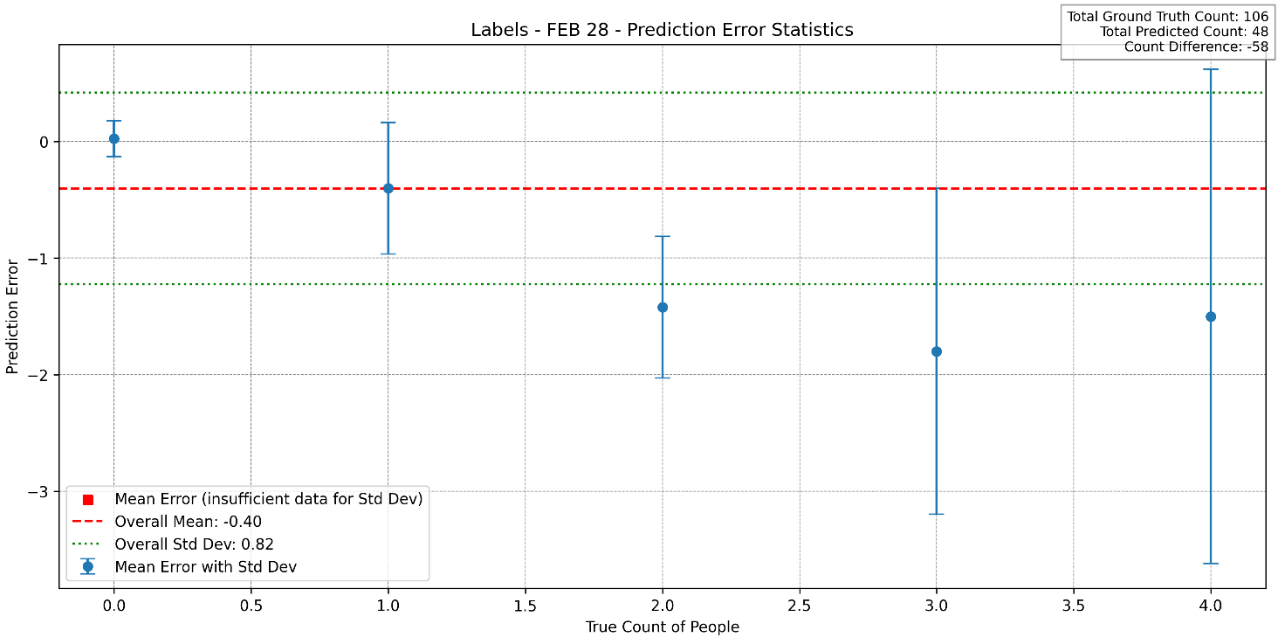
16 Feb 2024


People Count Analysis - Raw Data - Labels - FEB 16
Ground Truth (Raw)
Prediction (Raw)
Count
Time
2024-02-16 06:00
2024-02-16 08:00
2024-02-16 10:00
2024-02-16 12:00
2024-02-16 14:00
2024-02-16 16:00
2024-02-16 18:00

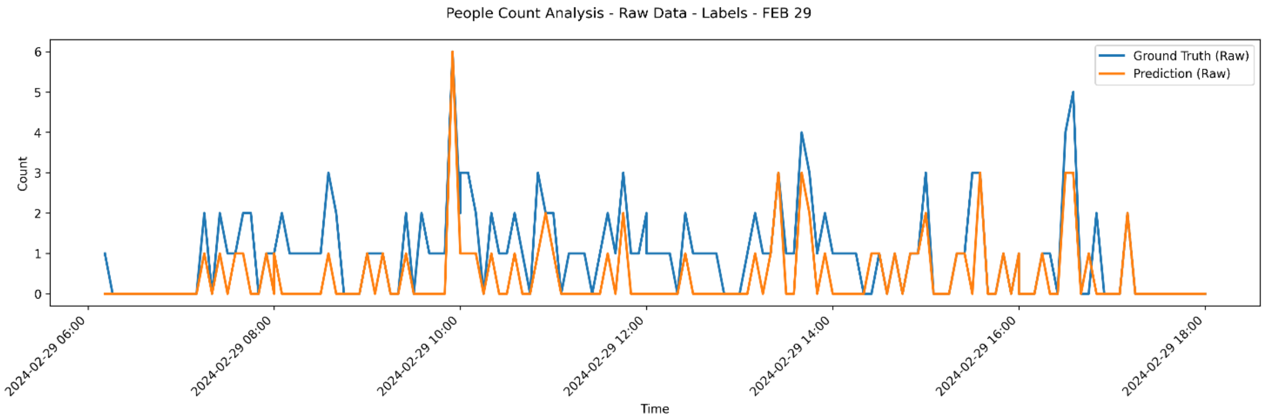

Labels - FEB 16 - Prediction Error Statistics
Total Ground Truth Count: 172
Total Predicted Count: 77
Count Difference: -95
Prediction Error
True Count of People
Mean Error (insufficient data for Std Dev)
Overall Mean: -0.62
Overall Std Dev: 0.89
Mean Error with Std Dev

28 Feb 2024

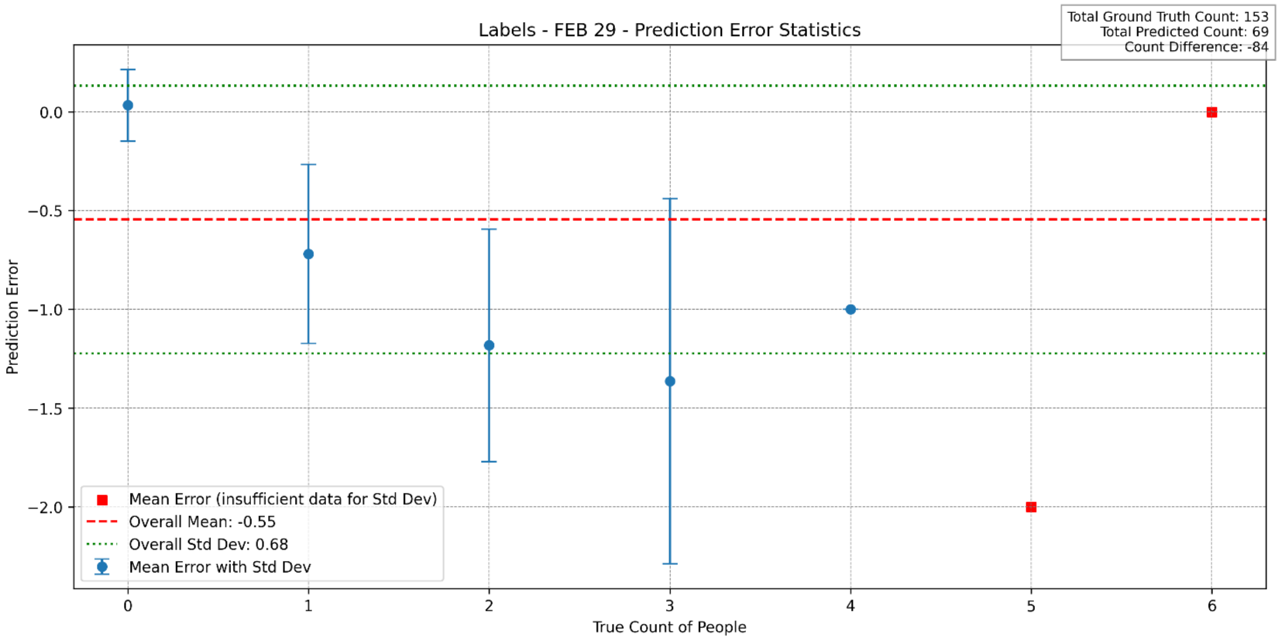

People Count Analysis - Raw Data - Labels - FEB 28
Ground Truth (Raw)
Prediction (Raw)
Count
Time
2024-02-28 06:00
2024-02-28 08:00
2024-02-28 10:00
2024-02-28 12:00
2024-02-28 14:00
2024-02-28 16:00
2024-02-28 18:00


Labels - FEB 28 - Prediction Error Statistics
Total Ground Truth Count: 106
Total Predicted Count: 48
Count Difference: -58
Mean Error (insufficient data for Std Dev)
Overall Mean: -0.40
Overall Std Dev: 0.82
Mean Error with Std Dev
Prediction Error
True Count of People

29 Feb 2024

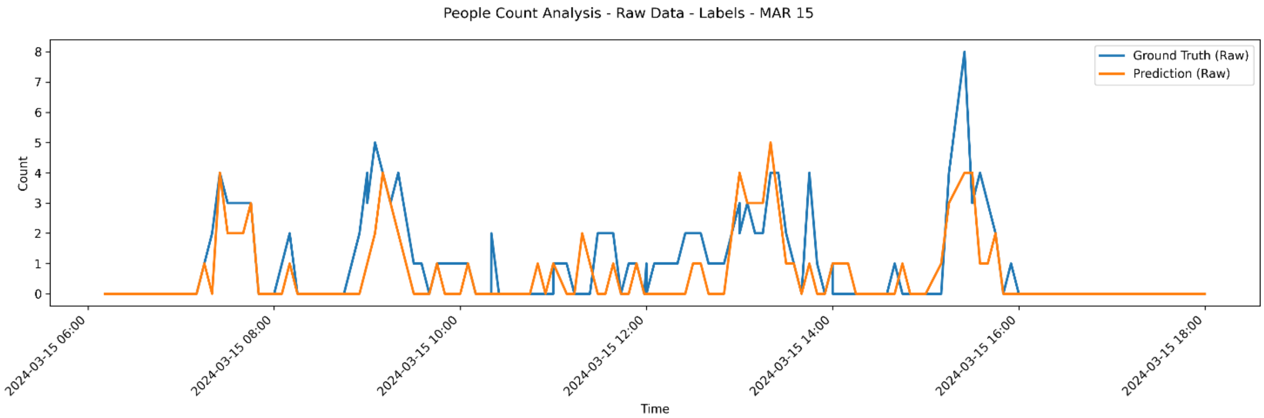


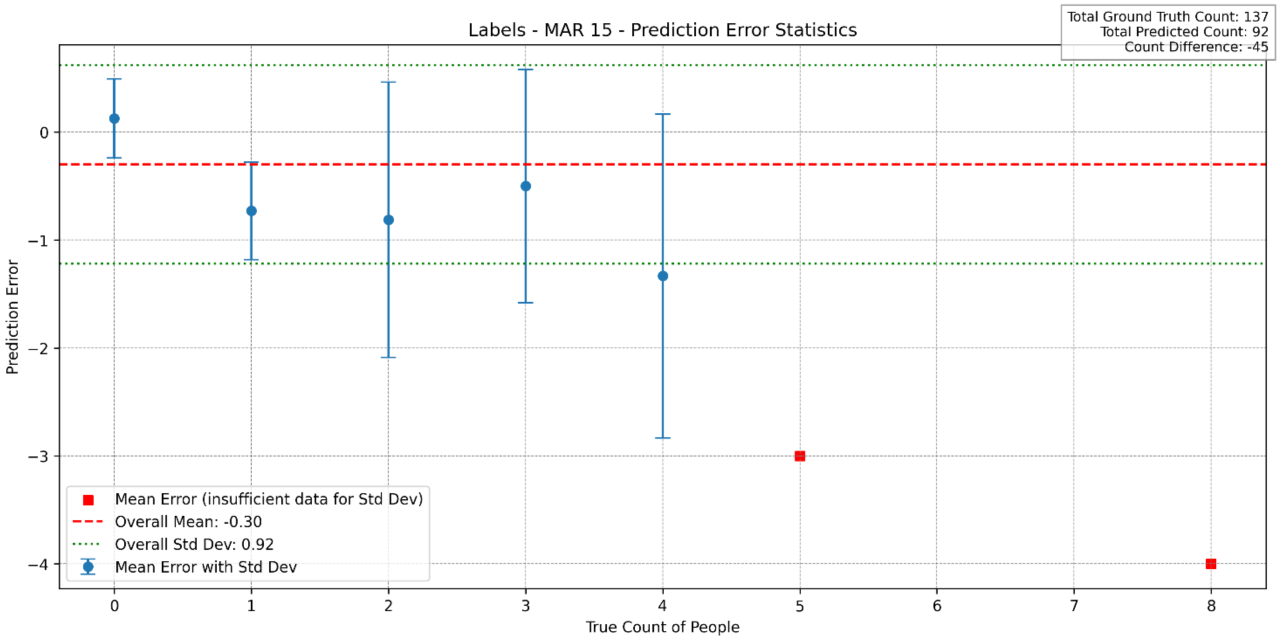
People Count Analysis - Raw Data - Labels - FEB 29
Ground Truth (Raw)
Prediction (Raw)
Count
Time
2024-02-29 06:00
2024-02-29 08:00
2024-02-29 10:00
2024-02-29 12:00
2024-02-29 14:00
2024-02-29 16:00
2024-02-29 18:00



Labels - FEB 29 - Prediction Error Statistics
Total Ground Truth Count: 153
Total Predicted Count: 69
Count Difference: -84
Mean Error (insufficient data for Std Dev)
Overall Mean: -0.55
Overall Std Dev: 0.68
Mean Error with Std Dev
Prediction Error
True Count of People

15 Mar 2024

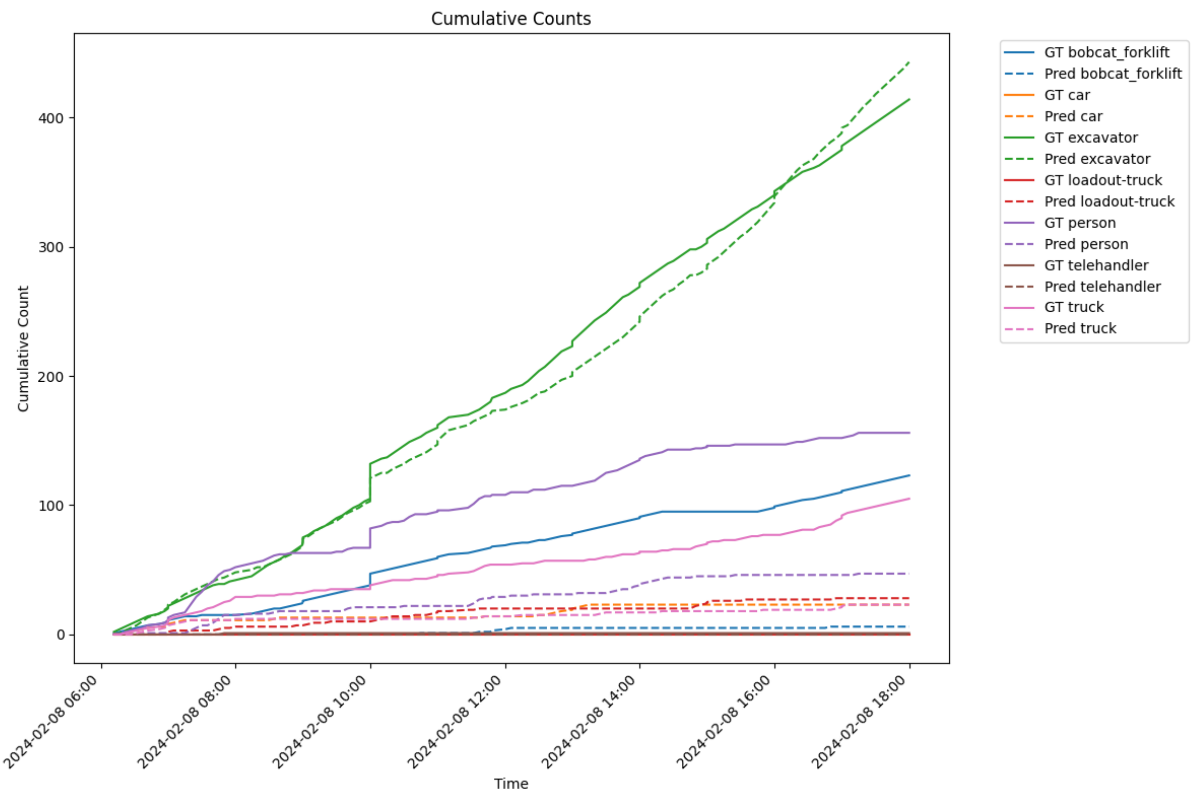

People Count Analysis - Raw Data - Labels - MAR 15
Ground Truth (Raw)
Prediction (Raw)
Count
Time
2024-03-15 06:00
2024-03-15 08:00
2024-03-15 10:00
2024-03-15 12:00
2024-03-15 14:00
2024-03-15 16:00
2024-03-15 18:00

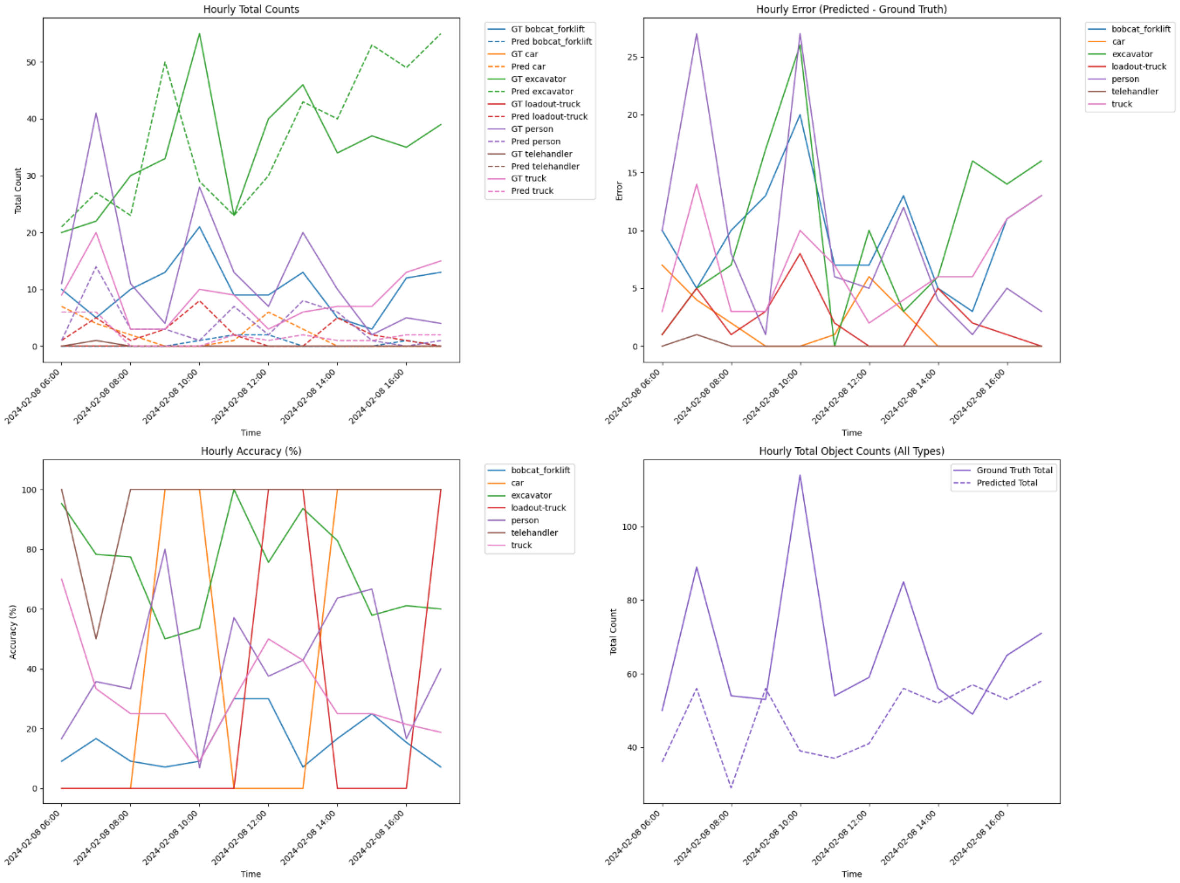

Labels - MAR 15 - Prediction Error Statistics
Total Ground Truth Count: 137
Total Predicted Count: 92
Count Difference: -45
Mean Error (insufficient data for Std Dev)
Overall Mean: -0.30
Overall Std Dev: 0.92
Mean Error with Std Dev
Prediction Error
True Count of People

Object Detection Analysis

8 Feb 2024

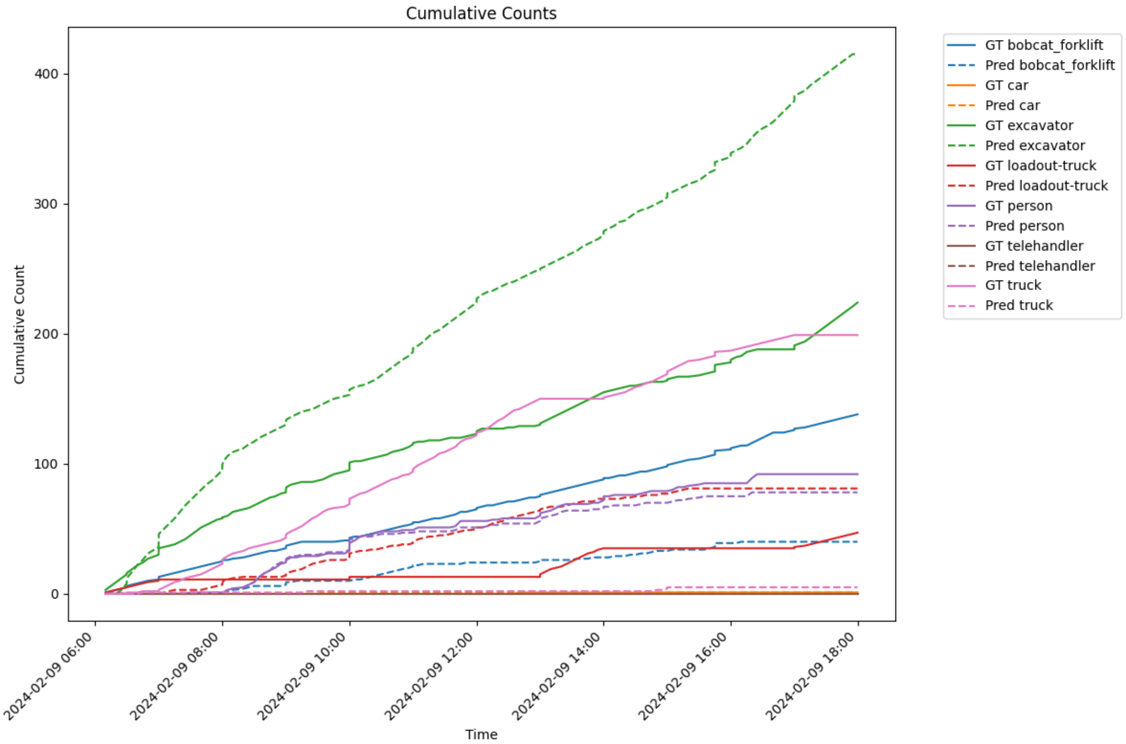
Object	Total Count Error	Mean Count Difference	RMSE	Correlation	R squared	Overcounting Rate (%)	Undercounting Rate (%)
bobcat_forklift	-117.00	-0.77	0.88	0.10	-3.99	0.00	76.97
car	23.00	0.15	0.39	0.00	0.00	15.13	0.00
excavator	29.00	0.19	1.13	0.35	-1.31	39.47	27.63
loadout-truck	28.00	0.18	0.44	0.00	0.00	17.76	0.00
person	-109.00	-0.72	1.18	0.64	0.04	0.00	48.03
telehandler	-1.00	-0.01	0.08	0.00	-0.01	0.00	0.66
truck	-82.00	-0.54	0.80	0.49	-0.39	0.00	48.68

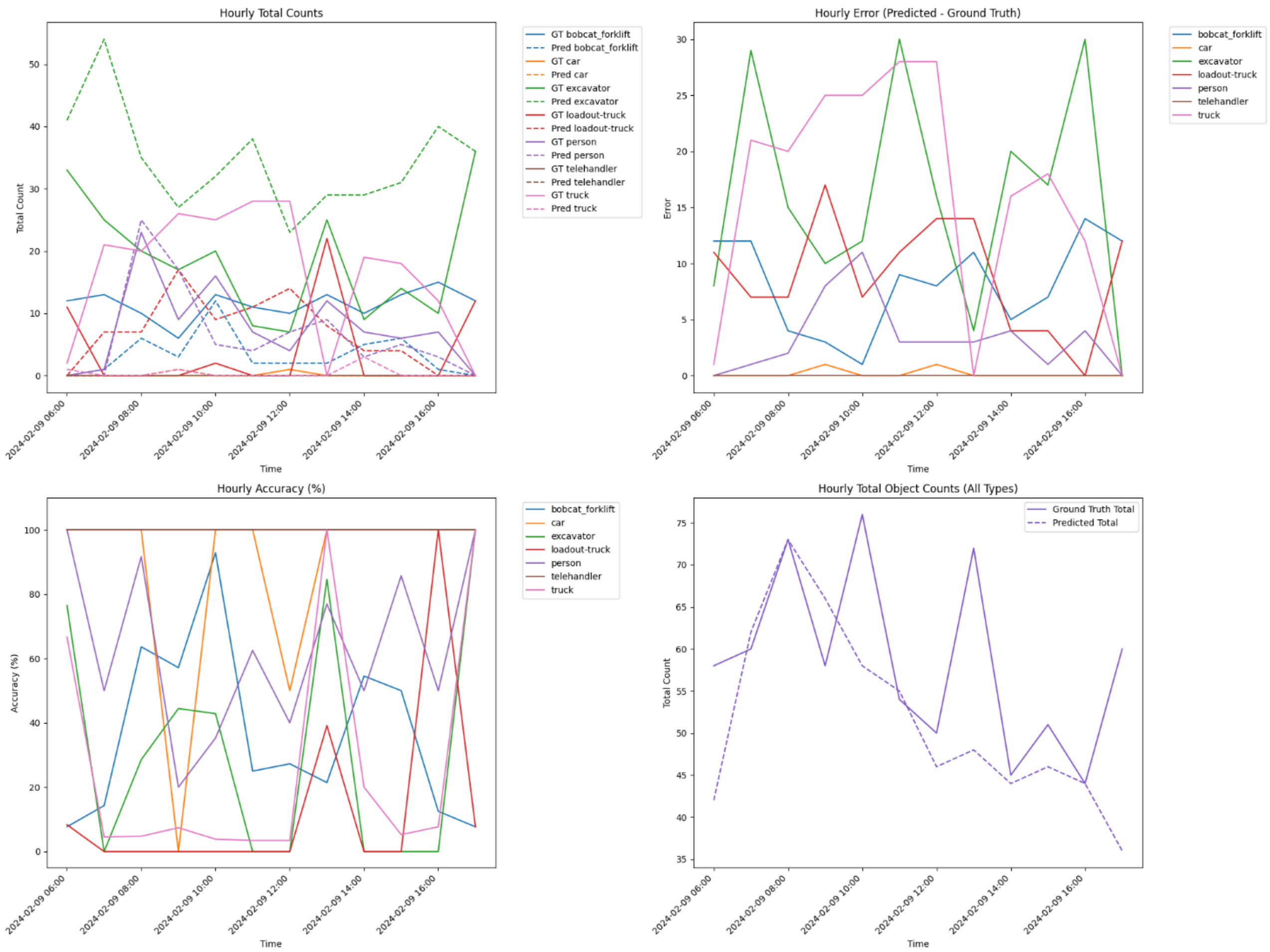




9 Feb 2024

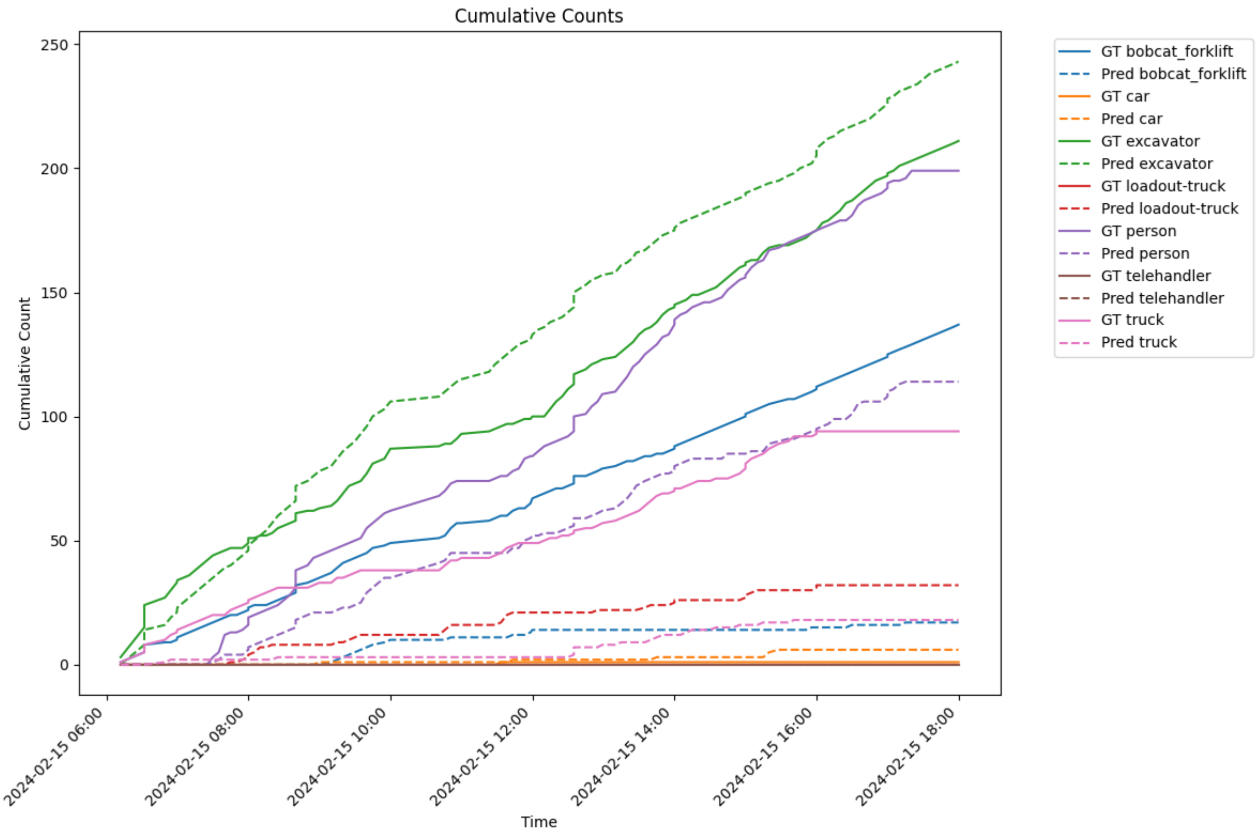
Object	Total Count Error	Mean Count Difference	RMSE	Correlation	R squared	Overcounting Rate (%)	Undercounting Rate (%)
bobcat_forklift	-98.00	-0.62	0.85	0.10	-2.97	1.27	59.87
car	0.00	0.00	0.11	-0.01	-1.01	0.64	0.64
excavator	191.00	1.22	1.80	0.21	-2.34	68.79	3.82
loadout-truck	34.00	0.22	0.87	-0.08	-1.36	40.76	22.29
person	-14.00	-0.09	0.55	0.83	0.68	3.18	10.83
telehandler	0.00	0.00	0.00	0.00	0.00	0.00	0.00
truck	-194.00	-1.24	1.53	0.15	-1.81	0.00	75.16

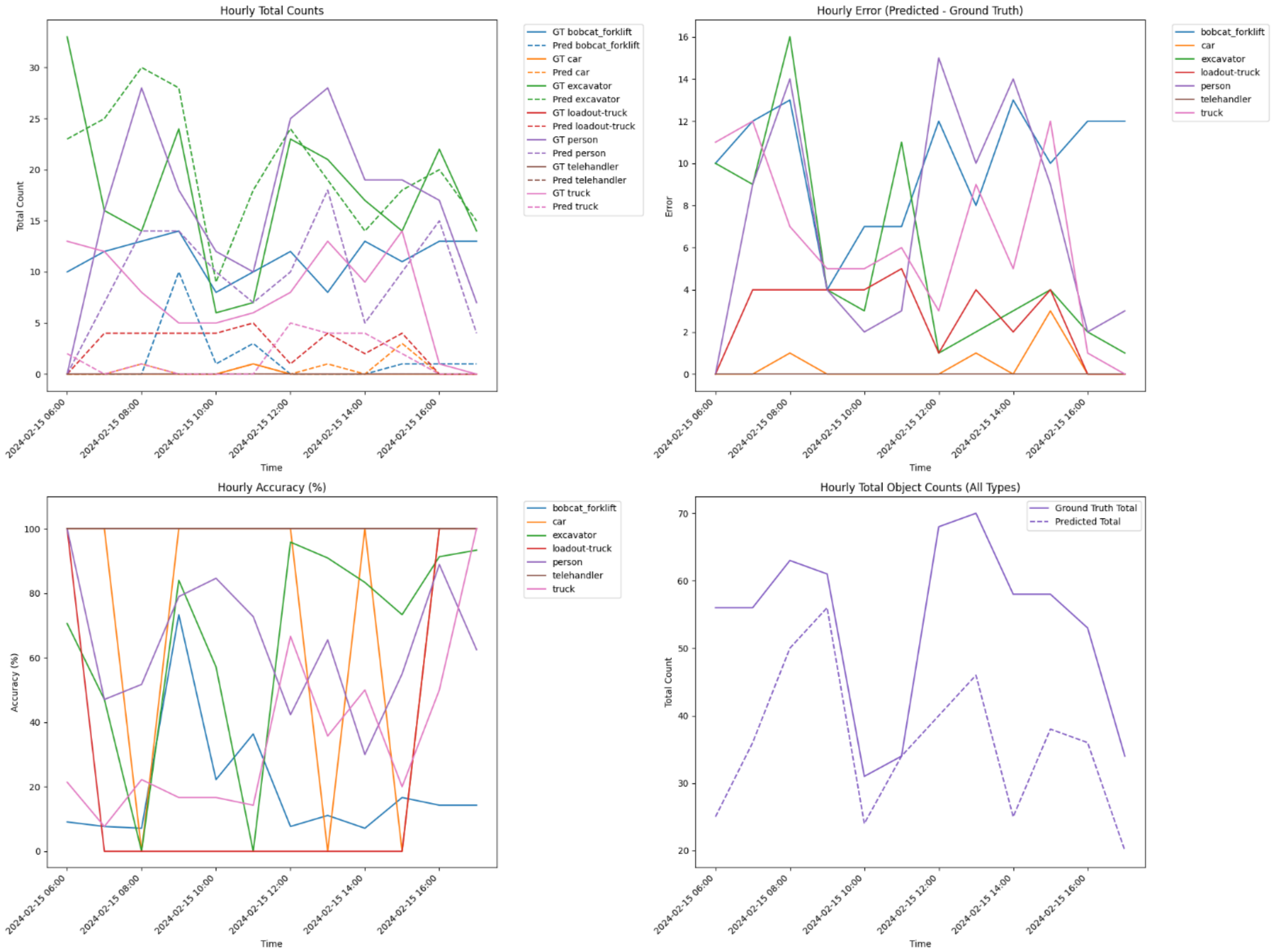

Cumulative Counts
Cumulative Count
Time
GT bobcat_forklift
Pred bobcat_forklift
GT car
Pred car
GT excavator
Pred excavator
GT loadout-truck
Pred loadout-truck
GT person
Pred person
GT telehandler
Pred telehandler
GT truck
Pred truck


Hourly Total Counts
Total Count
Time
Hourly Error (Predicted - Ground Truth)
Error
Hourly Accuracy (%)
Accuracy (%)
Hourly Total Object Counts (All Types)
Ground Truth Total
Predicted Total
bobcat_forklift
car
excavator
loadout-truck
person
telehandler
truck

15 Feb 2024

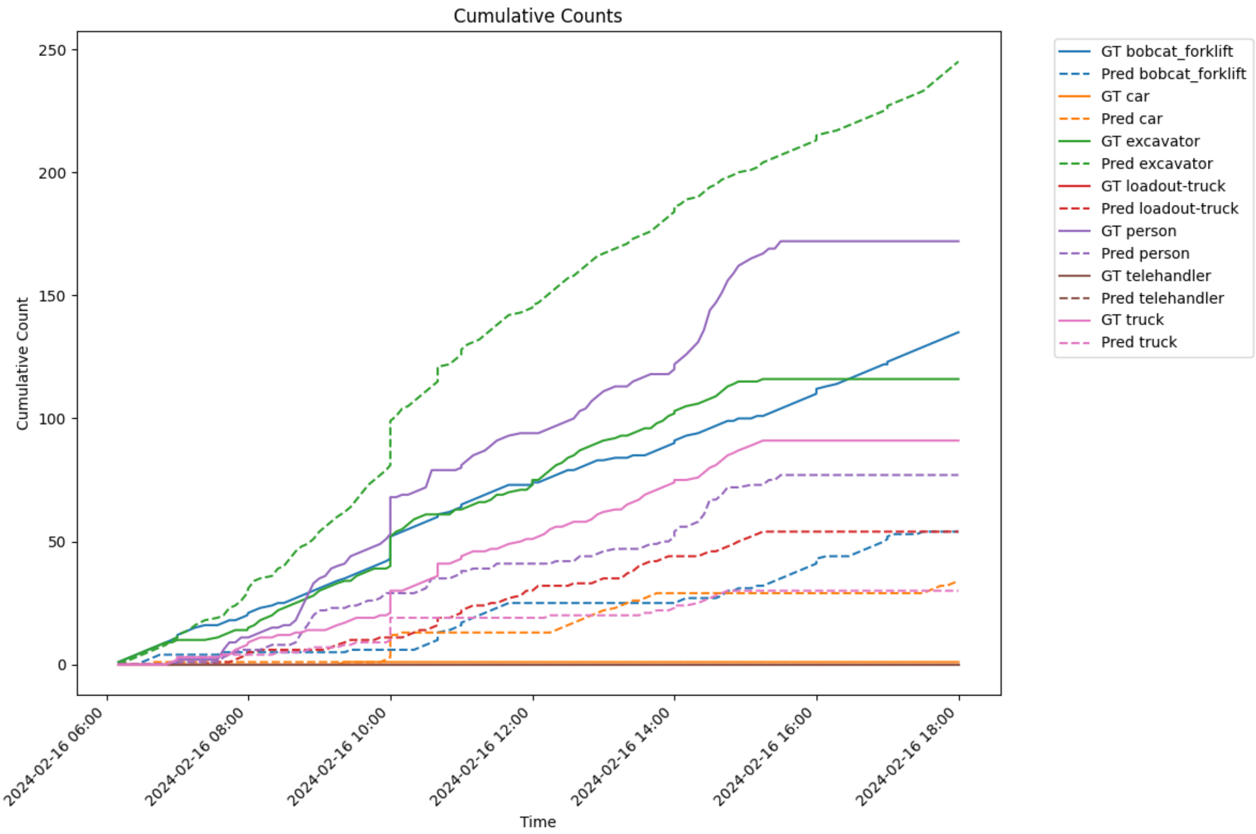
Object	Total Count Error	Mean Count Difference	RMSE	Correlation	R squared	Overcounting Rate (%)	Undercounting Rate (%)
bobcat_forklift	-120.00	-0.86	0.95	0.47	-3.85	0.00	84.17
car	5.00	0.04	0.25	-0.02	-8.07	3.60	0.72
excavator	32.00	0.23	1.07	0.17	-0.35	41.01	25.90
loadout-truck	32.00	0.23	0.56	0.00	0.00	19.42	0.00
person	-85.00	-0.61	1.06	0.73	0.30	2.88	48.92
telehandler	0.00	0.00	0.00	0.00	0.00	0.00	0.00
truck	-76.00	-0.55	0.86	0.28	-0.63	1.44	48.20

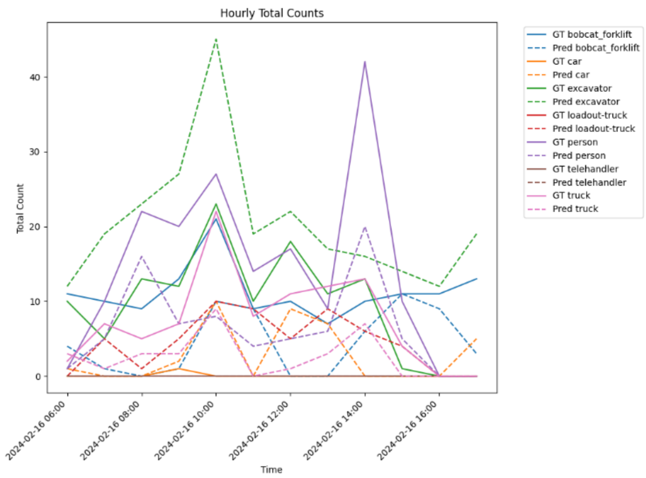


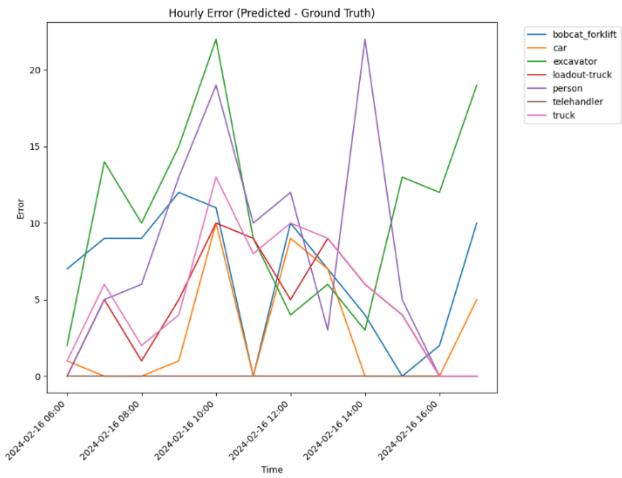


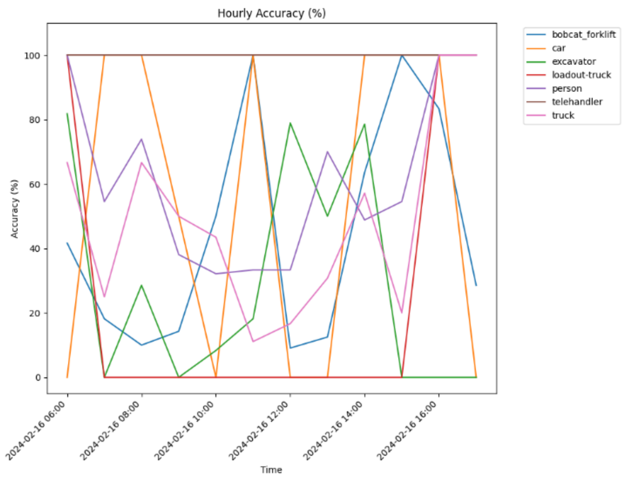
16 Feb 2024

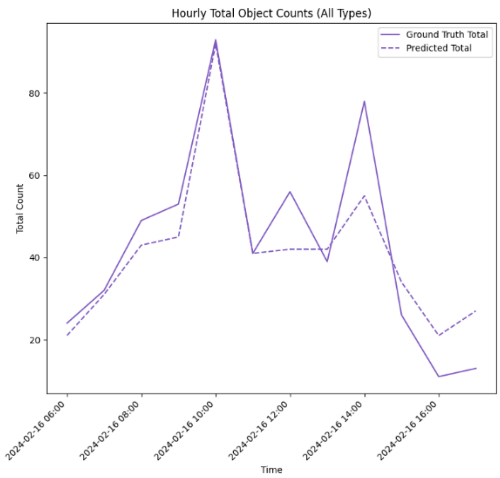
Object	Total Count Error	Mean Count Difference	RMSE	Correlation	R squared	Overcounting Rate (%)	Undercounting Rate (%)
bobcat_forklift	-81.00	-0.53	0.76	0.15	-4.34	2.60	55.19
car	33.00	0.21	0.48	-0.04	-34.23	22.08	0.65
excavator	129.00	0.84	1.16	0.28	-1.70	68.18	4.55
loadout-truck	54.00	0.35	0.64	0.00	0.00	31.82	0.00
person	-95.00	-0.62	1.08	0.81	0.46	1.95	42.21
telehandler	0.00	0.00	0.00	0.00	0.00	0.00	0.00
truck	-61.00	-0.40	0.70	0.45	-0.22	0.65	36.36


Cumulative Counts
Cumulative Count
Time
GT bobcat_forklift
Pred bobcat_forklift
GT car
Pred car
GT excavator
Pred excavator
GT loadout-truck
Pred loadout-truck
GT person
Pred person
GT telehandler
Pred telehandler
GT truck
Pred truck


Hourly Total Counts
Total Count
Time
GT bobcat_forklift
Pred bobcat_forklift
GT car
Pred car
GT excavator
Pred excavator
GT loadout-truck
Pred loadout-truck
GT person
Pred person
GT telehandler
Pred telehandler
GT truck
Pred truck

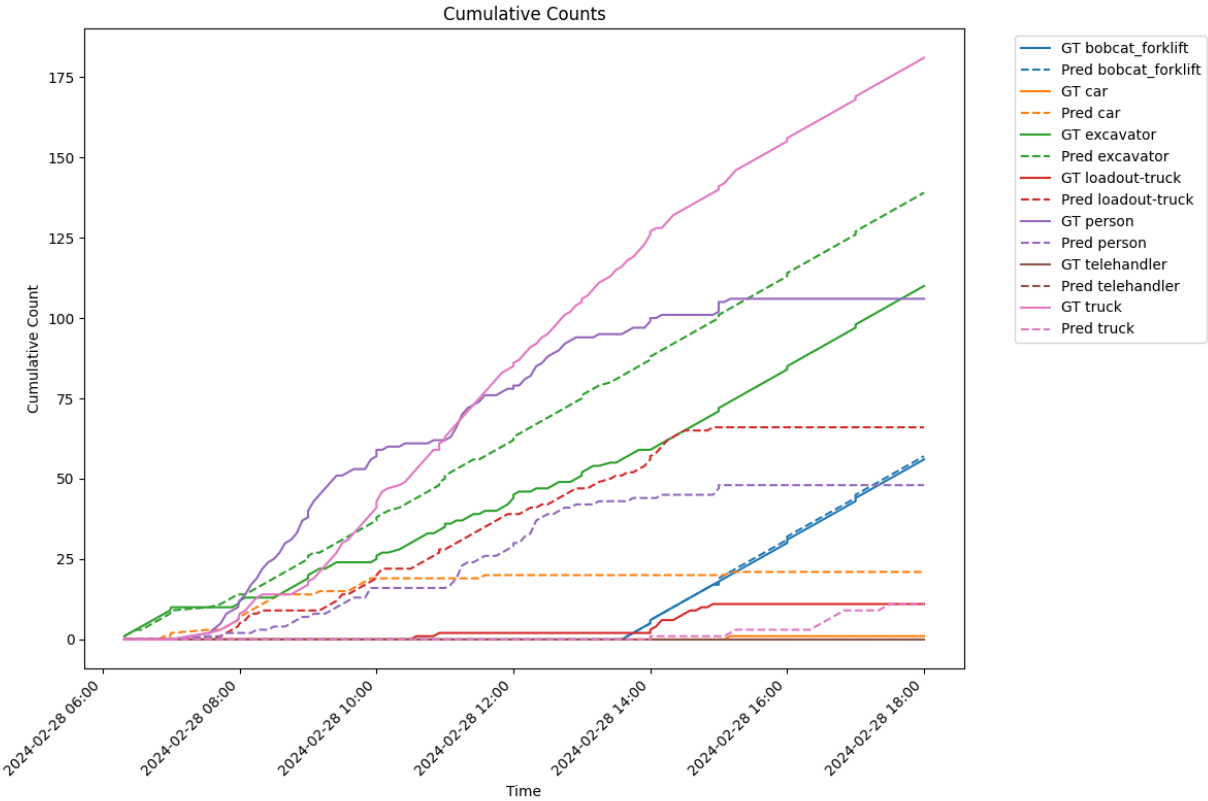

Hourly Error (Predicted - Ground Truth)
Error
Time
bobcat_forklift
car
excavator
loadout-truck
person
telehandler
truck

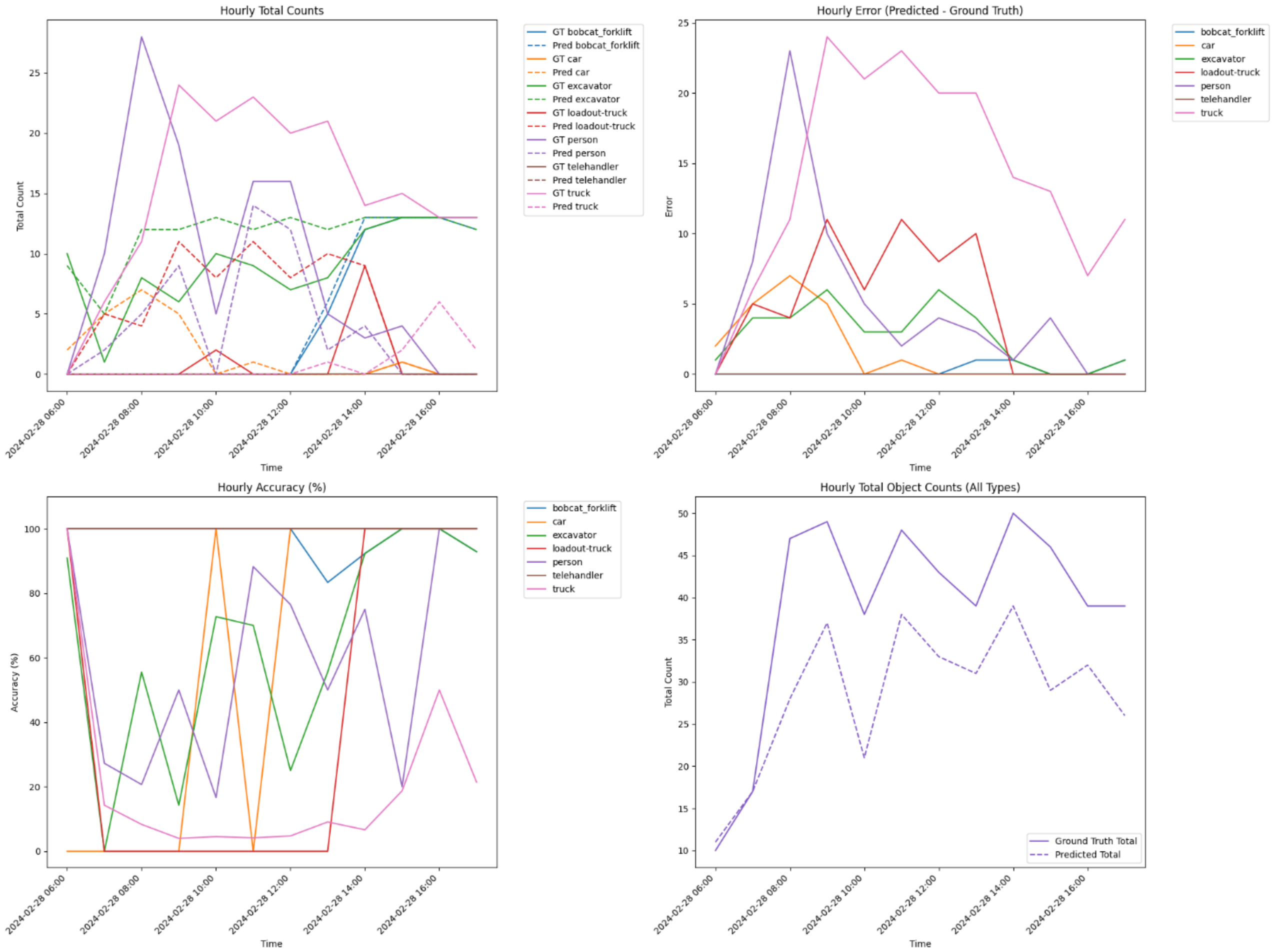

Hourly Accuracy (%)
Accuracy (%)
Time
bobcat_forklift
car
excavator
loadout-truck
person
telehandler
truck


Hourly Total Object Counts (All Types)
Total Count
Time
Ground Truth Total
Predicted Total

28 Feb 2024

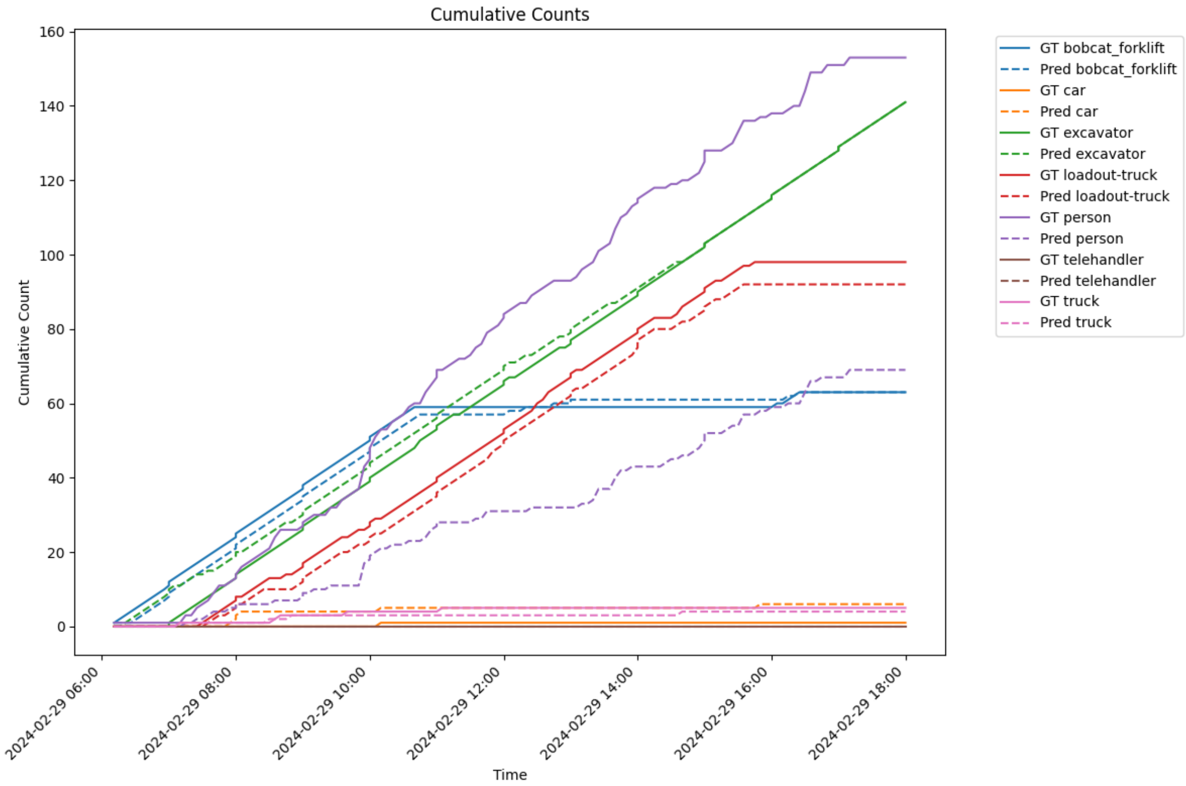
Object	Total Count Error	Mean Count Difference	RMSE	Correlation	R squared	Overcounting Rate (%)	Undercounting Rate (%)
bobcat_forklift	1.00	0.01	0.08	0.99	0.97	0.69	0.00
car	20.00	0.14	0.37	0.20	-19.14	13.89	0.00
excavator	29.00	0.20	0.52	-0.02	-0.39	23.61	3.47
loadout-truck	55.00	0.38	0.69	0.25	-4.67	36.11	1.39
person	-58.00	-0.40	0.91	0.60	0.20	2.78	27.78
telehandler	0.00	0.00	0.00	0.00	0.00	0.00	0.00
truck	-170.00	-1.18	1.39	-0.03	-3.15	0.00	81.94

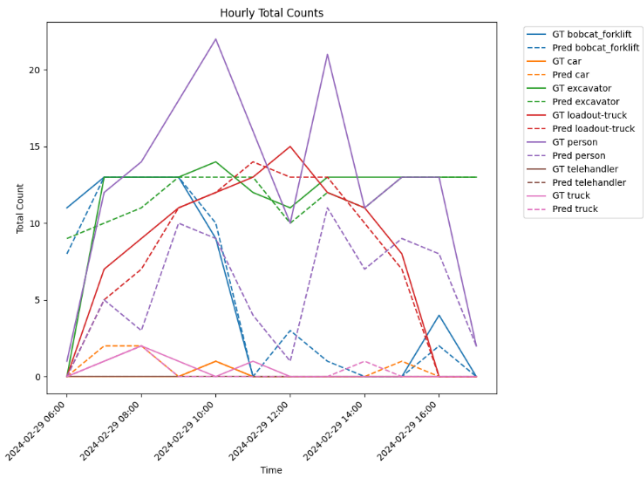


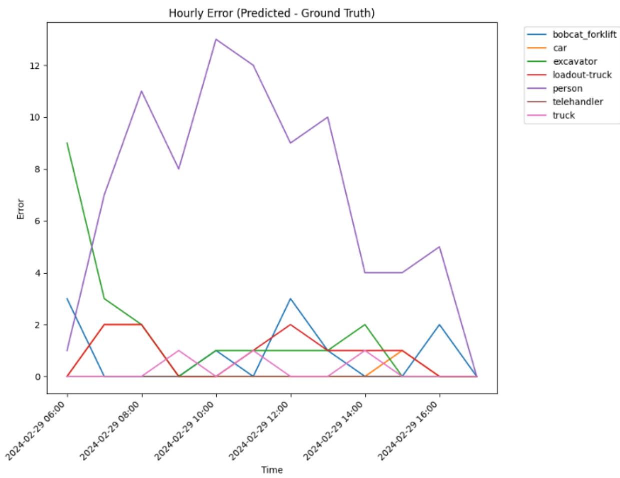


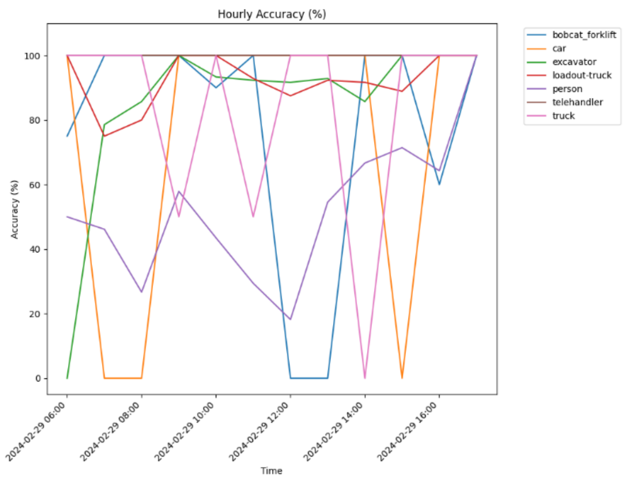
29 Feb 2024

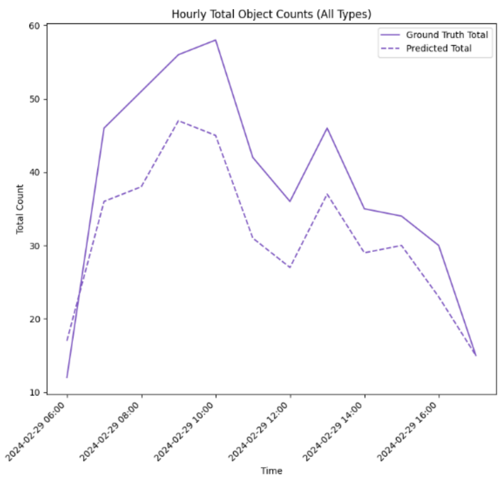
Object	Total Count Error	Mean Count Difference	RMSE	Correlation	R squared	Overcounting Rate (%)	Undercounting Rate (%)
bobcat_forklift	0.00	0.00	0.25	0.87	0.73	3.25	3.25
car	5.00	0.03	0.18	0.40	-4.03	3.25	0.00
excavator	0.00	0.00	0.36	0.23	-0.44	6.49	6.49
loadout-truck	-6.00	-0.04	0.28	0.86	0.71	1.95	5.84
person	-84.00	-0.55	0.87	0.79	0.37	1.30	47.40
telehandler	0.00	0.00	0.00	0.00	0.00	0.00	0.00
truck	-1.00	-0.01	0.21	0.20	-0.45	1.95	2.60


Cumulative Counts
Cumulative Count
Time
GT bobcat_forklift
Pred bobcat_forklift
GT car
Pred car
GT excavator
Pred excavator
GT loadout-truck
Pred loadout-truck
GT person
Pred person
GT telehandler
Pred telehandler
GT truck
Pred truck


Hourly Total Counts
Total Count
Time

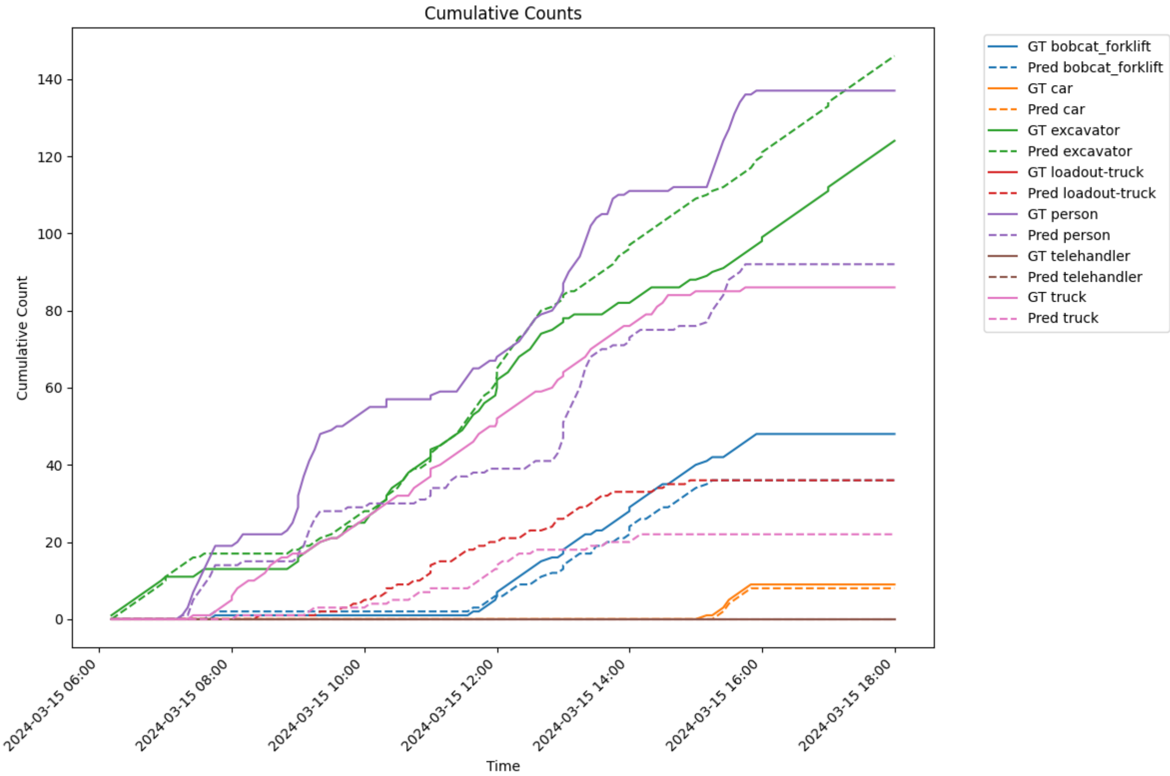

Hourly Error (Predicted - Ground Truth)
Error
Time

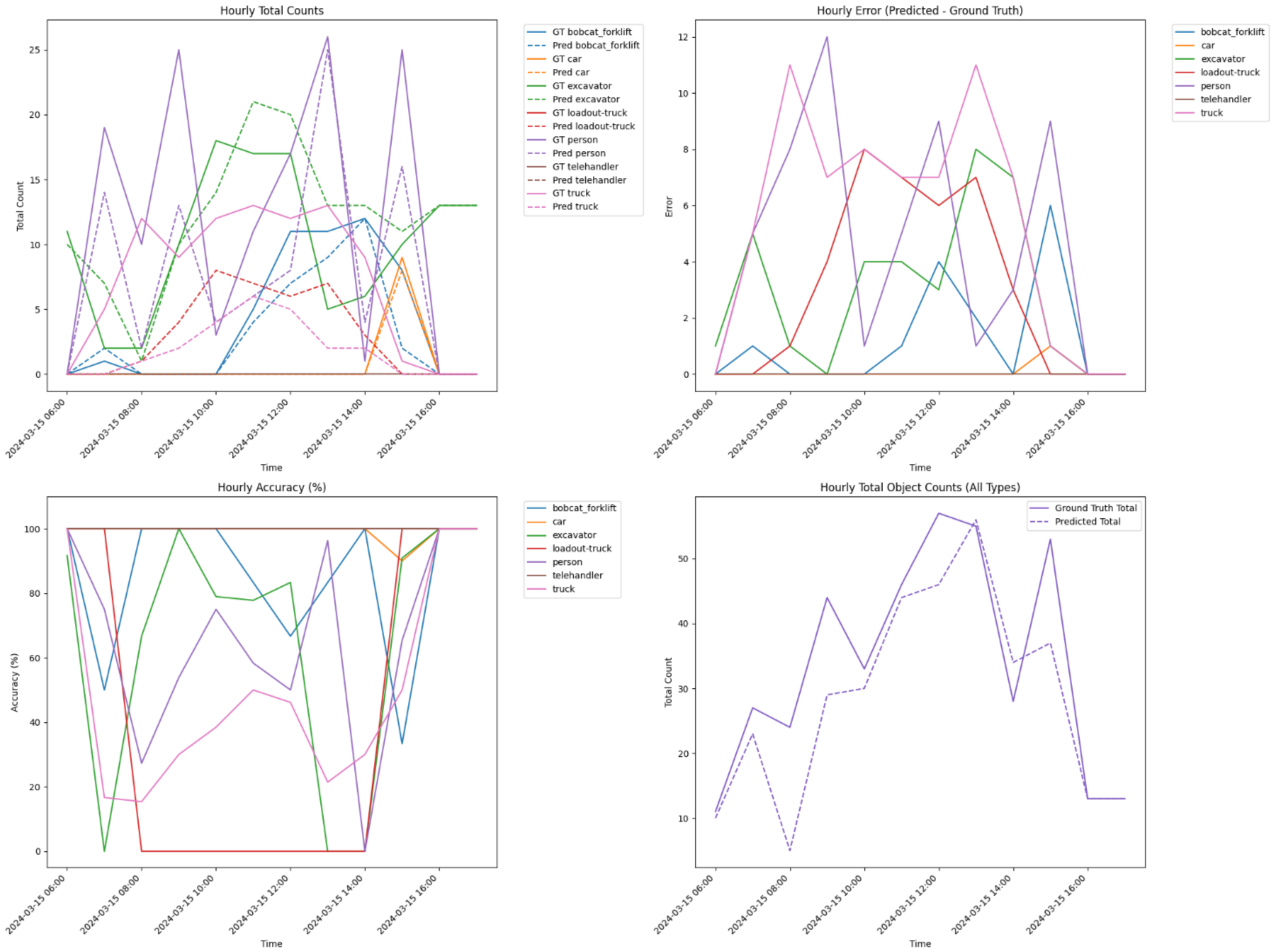

Hourly Accuracy (%)
Accuracy (%)
Time


Hourly Total Object Counts (All Types)
Total Count
Time
Ground Truth Total
Predicted Total

15 Mar 2024

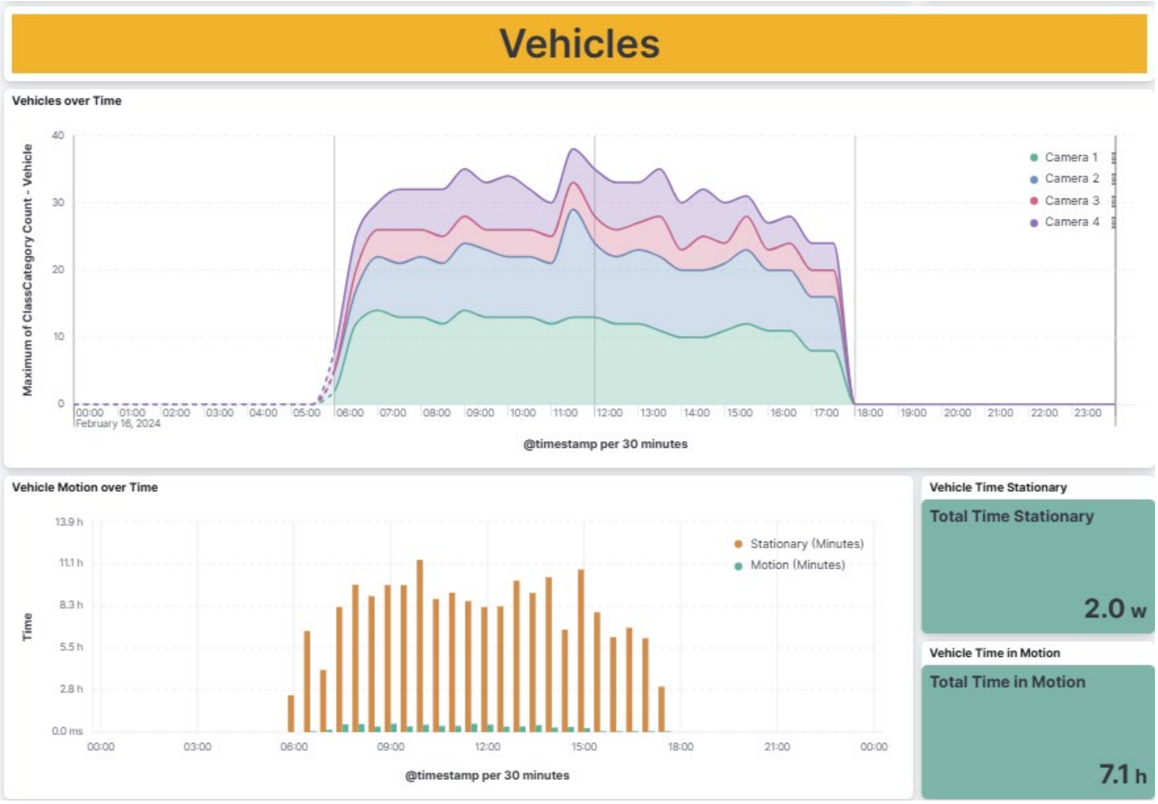
Object	Total Count Error	Mean Count Difference	RMSE	Correlation	R squared	Overcounting Rate (%)	Undercounting Rate (%)
bobcat_forklift	-12.00	-0.08	0.35	0.73	0.45	2.00	10.00
car	-1.00	-0.01	0.08	0.96	0.92	0.00	0.67
excavator	22.00	0.15	0.57	0.52	0.03	22.67	7.33
loadout-truck	36.00	0.24	0.50	0.00	0.00	23.33	0.00
person	-45.00	-0.30	0.96	0.75	0.52	10.67	28.67
telehandler	0.00	0.00	0.00	0.00	0.00	0.00	0.00
truck	-64.00	-0.43	0.70	0.39	-0.40	0.67	40.67



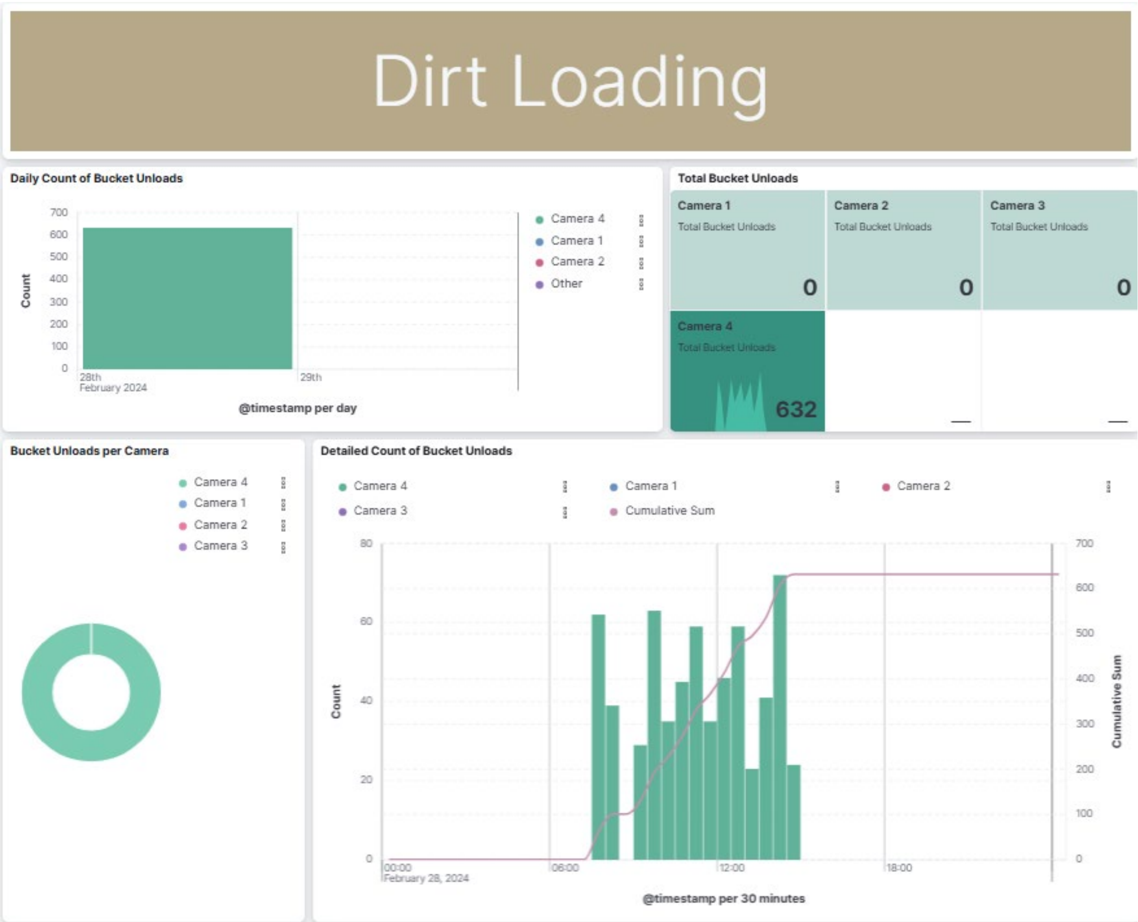

Hourly Total Counts
Total Count
Time
GT bobcat_forklift
Pred bobcat_forklift
GT car
Pred car
GT excavator
Pred excavator
GT loadout-truck
Pred loadout-truck
GT person
Pred person
GT telehandler
Pred telehandler
GT truck
Pred truck
Hourly Error (Predicted - Ground Truth)
Error
bobcat_forklift
car
excavator
loadout-truck
person
telehandler
truck
Hourly Accuracy (%)
Accuracy (%)
Hourly Total Object Counts (All Types)
Ground Truth Total
Predicted Total
2024-03-15 06:00
2024-03-15 08:00
2024-03-15 10:00
2024-03-15 12:00
2024-03-15 14:00
2024-03-15 16:00

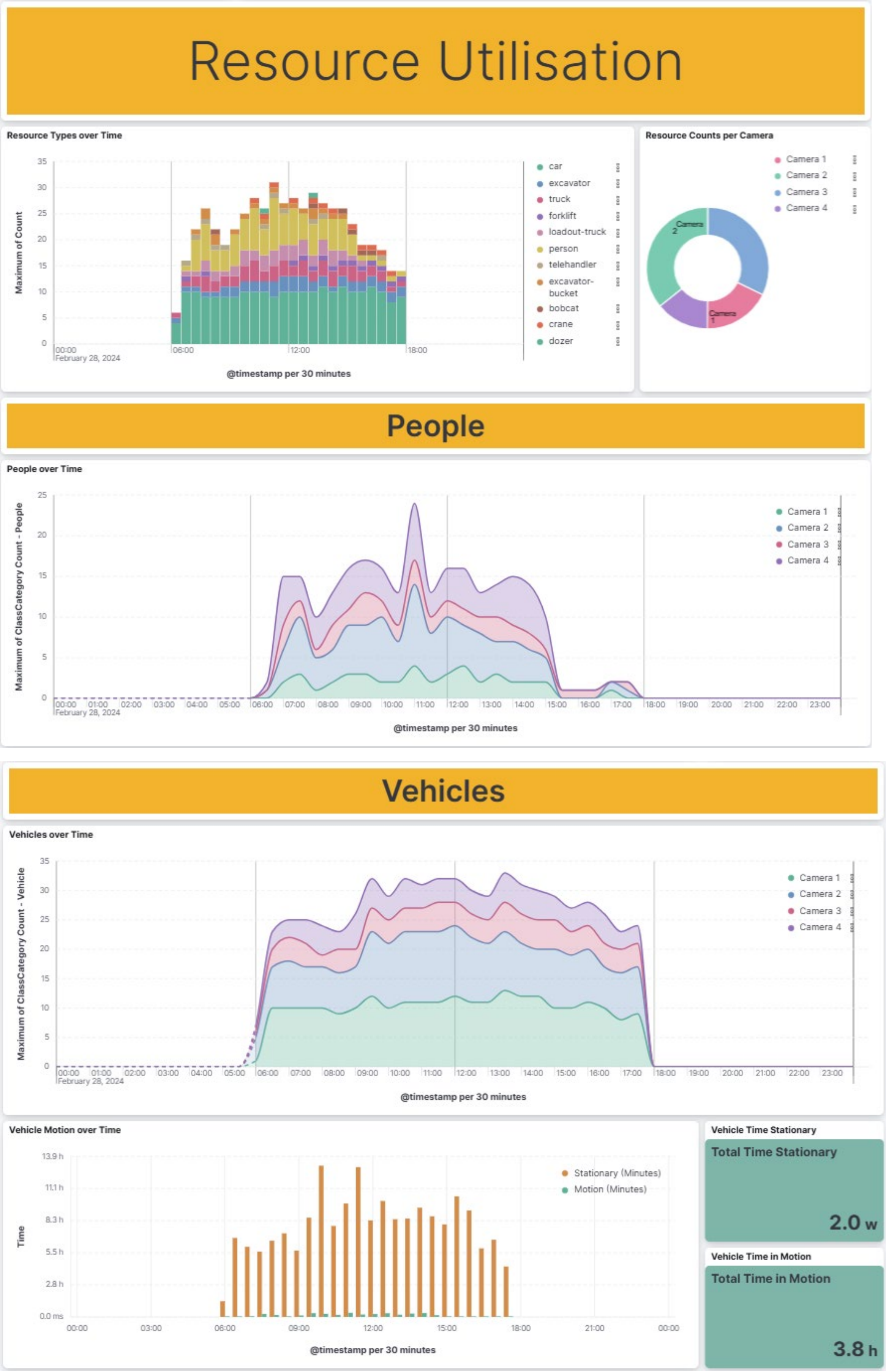
Appendix G – Visualisation Dashboard Additional Days

16 Feb 2024


Vehicles
Vehicles over Time
Maximum of ClassCategory Count - Vehicle
February 16, 2024
@timestamp per 30 minutes
Camera 1
Camera 2
Camera 3
Camera 4
Vehicle Motion over Time
Time
Stationary (Minutes)
Motion (Minutes)
@timestamp per 30 minutes
Vehicle Time Stationary
Total Time Stationary
2.0 w
Vehicle Time in Motion
Total Time in Motion
7.1 h

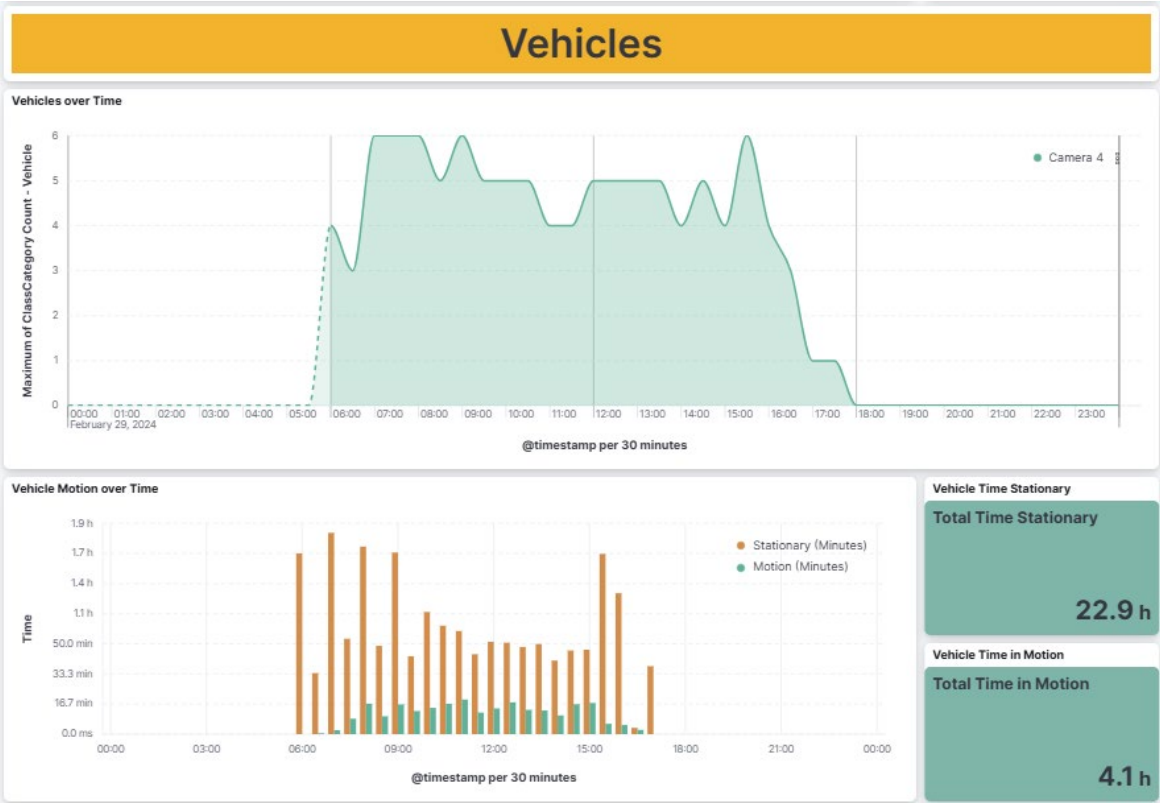
28 Feb 2024


Dirt Loading
Daily Count of Bucket Unloads
Count
28th
February 2024
29th
@timestamp per day
Camera 4
Camera 1
Camera 2
Other
Total Bucket Unloads
Camera 1
Total Bucket Unloads
0
Camera 2
Total Bucket Unloads
0
Camera 3
Total Bucket Unloads
0
Camera 4
Total Bucket Unloads
632
Bucket Unloads per Camera
Camera 4
Camera 1
Camera 2
Camera 3
Detailed Count of Bucket Unloads
Camera 4
Camera 1
Camera 2
Camera 3
Cumulative Sum
Count
Cumulative Sum
February 28, 2024
@timestamp per 30 minutes

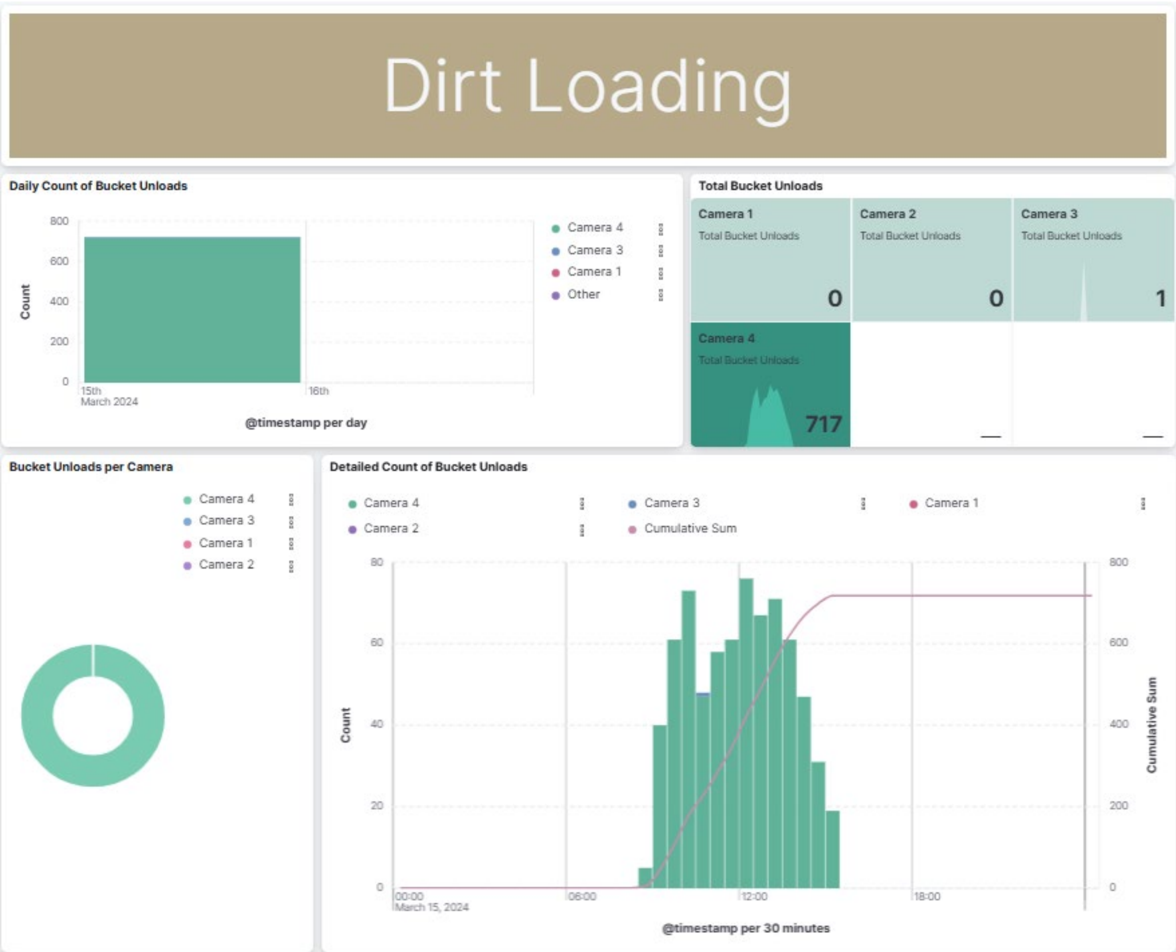

Resource Utilisation
Resource Types over Time
Maximum of Count
@timestamp per 30 minutes
car
excavator
truck
forklift
loadout-truck
person
telehandler
excavator-bucket
bobcat
crane
dozer
Resource Counts per Camera
Camera 1
Camera 2
Camera 3
Camera 4
People
People over Time
Maximum of ClassCategory Count - People
@timestamp per 30 minutes
February 28, 2024
Vehicles
Vehicles over Time
Maximum of ClassCategory Count - Vehicle
@timestamp per 30 minutes
Vehicle Motion over Time
Time
Stationary (Minutes)
Motion (Minutes)
@timestamp per 30 minutes
Vehicle Time Stationary
Total Time Stationary
2.0 w
Vehicle Time in Motion
Total Time in Motion
3.8 h

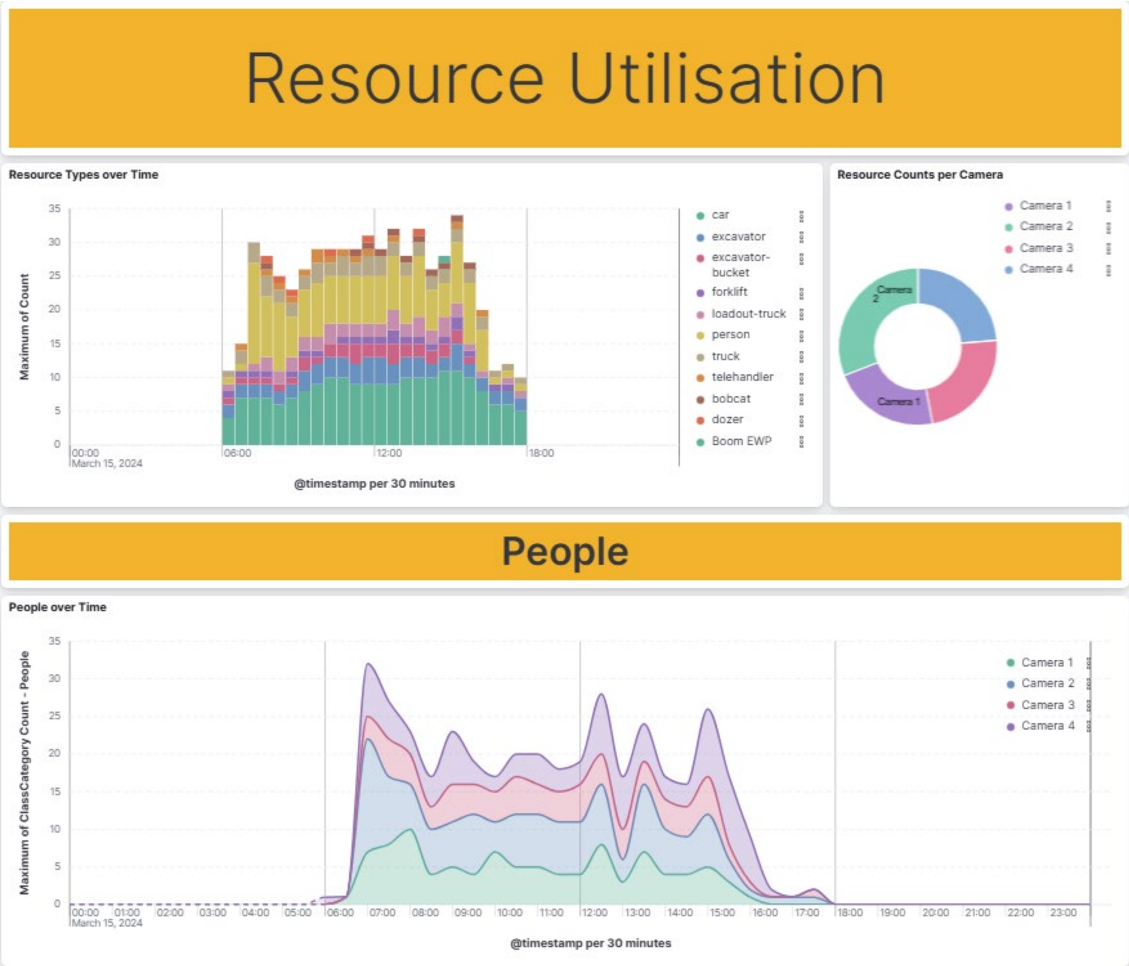
29 Feb 2024

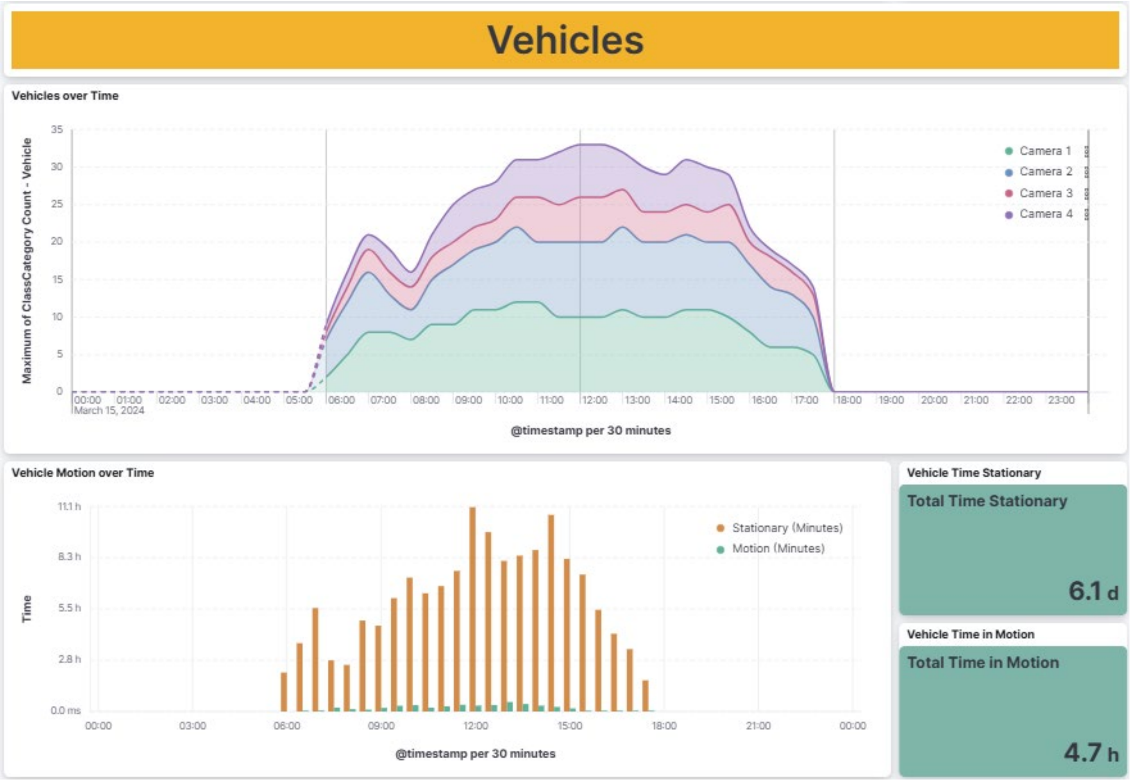

Dirt Loading
Daily Count of Bucket Unloads
Camera 4
Count
@timestamp per day
29th February 2024
1st March 2024
Total Bucket Unloads
Camera 4
Total Bucket Unloads
1,118
Bucket Unloads per Camera
Camera 4
Camera 4 100%
Detailed Count of Bucket Unloads
Camera 4
Cumulative Sum
Count
Cumulative Sum
00:00 February 29, 2024
06:00
12:00
18:00
@timestamp per 30 minutes
Resource Utilisation
Resource Types over Time
Maximum of Count
car
excavator
forklift
loadout-truck
telehandler
truck
dozer
excavator-bucket
person
bobcat
Boom EWP
00:00 February 29, 2024
06:00
12:00
18:00
@timestamp per 30 minutes
Resource Counts per Camera
Camera 4
Camera 4
People
People over Time
Maximum of ClassCategory Count - People
Camera 4
00:00 February 29, 2024
@timestamp per 30 minutes


Vehicles
Vehicles over Time
Maximum of ClassCategory Count - Vehicle
Camera 4
February 29, 2024
@timestamp per 30 minutes
Vehicle Motion over Time
Time
Stationary (Minutes)
Motion (Minutes)
@timestamp per 30 minutes
Vehicle Time Stationary
Total Time Stationary
22.9 h
Vehicle Time in Motion
Total Time in Motion
4.1 h

15 Mar 2024

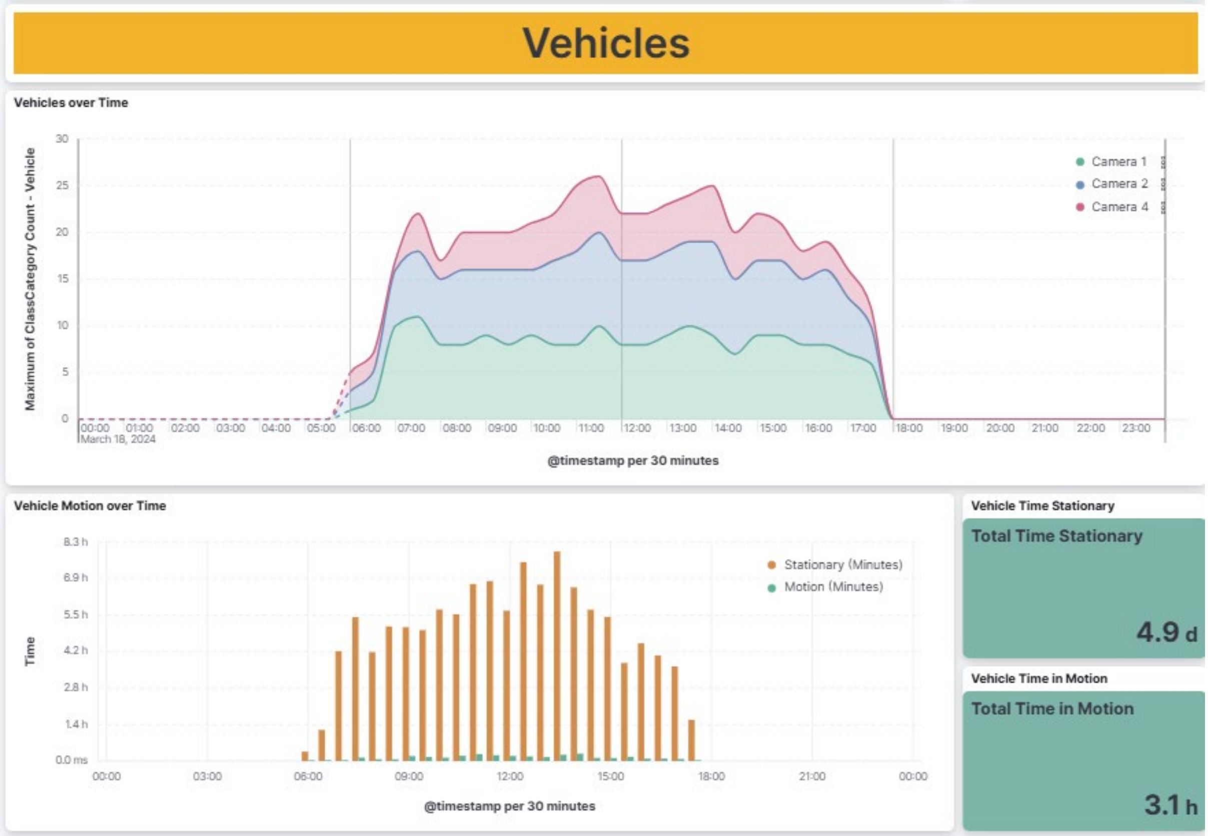

Dirt Loading
Daily Count of Bucket Unloads
Count
Camera 4
Camera 3
Camera 1
Other
15th
March 2024
16th
@timestamp per day
Total Bucket Unloads
Camera 1
Total Bucket Unloads
0
Camera 2
Total Bucket Unloads
0
Camera 3
Total Bucket Unloads
1
Camera 4
Total Bucket Unloads
717
Bucket Unloads per Camera
Camera 4
Camera 3
Camera 1
Camera 2
Detailed Count of Bucket Unloads
Camera 4
Camera 3
Camera 1
Camera 2
Cumulative Sum
Count
Cumulative Sum
March 15, 2024
@timestamp per 30 minutes


Resource Utilisation
Resource Types over Time
Maximum of Count
@timestamp per 30 minutes
00:00
March 15, 2024
06:00
12:00
18:00
car
excavator
excavator-bucket
forklift
loadout-truck
person
truck
telehandler
bobcat
dozer
Boom EWP
Resource Counts per Camera
Camera 1
Camera 2
Camera 3
Camera 4
People
People over Time
Maximum of ClassCategory Count - People
@timestamp per 30 minutes


Vehicles
Vehicles over Time
Maximum of ClassCategory Count - Vehicle
@timestamp per 30 minutes
Camera 1
Camera 2
Camera 3
Camera 4
Vehicle Motion over Time
Time
Stationary (Minutes)
Motion (Minutes)
@timestamp per 30 minutes
Vehicle Time Stationary
Total Time Stationary
6.1 d
Vehicle Time in Motion
Total Time in Motion
4.7 h

18 Mar 2024


Dirt Loading
Daily Count of Bucket Unloads
Count
@timestamp per day
Camera 4
Camera 1
Camera 2
Total Bucket Unloads
Camera 1
Total Bucket Unloads
0
Camera 2
Total Bucket Unloads
0
Camera 4
Total Bucket Unloads
389
Bucket Unloads per Camera
Detailed Count of Bucket Unloads
Cumulative Sum
@timestamp per 30 minutes
Resource Utilisation
Resource Types over Time
Maximum of Count
car
excavator
loadout-truck
person
truck
excavator-bucket
telehandler
dozer
crane
forklift
bobcat
Resource Counts per Camera
People
People over Time
Maximum of ClassCategory Count - People


Vehicles
Vehicles over Time
Maximum of ClassCategory Count - Vehicle
Camera 1
Camera 2
Camera 4
March 18, 2024
@timestamp per 30 minutes
Vehicle Motion over Time
Time
Stationary (Minutes)
Motion (Minutes)
@timestamp per 30 minutes
Vehicle Time Stationary
Total Time Stationary
4.9 d
Vehicle Time in Motion
Total Time in Motion
3.1 h

info@building40crc.org
www.building4pointzero.org
/building-4-0-crc