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USE OF COMPUTER VISION AND OBJECT DETECTION TO MEASURE CONSTRUCTION PRODUCTIVITY USING CREW BALANCE CHARTS

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ABSTRACT

Experts in the construction industry identify artificial intelligence (AI) technologies as a key strategy for improving productivity. In Chile, construction productivity has stagnated over the past two decades. This study explores the use of computer vision and a machine learning (ML) algorithm to measure productivity reliably, aiming to improve processes and support data-driven decision-making.

This research uses the YOLOv5 algorithm to detect workers' body postures from video and image data. Body postures are categorized as Productive or Contributory Work based on a predefined taxonomy. The algorithm was trained using 1,500 images extracted from 74 360-degree videos captured using a GoPro camera, representing over five hours of slab formwork installation. Experimental results achieved a mean average precision (mAP 0.5) exceeding 85%.

For productivity measurement, fixed-camera recordings captured images at five-second intervals. YOLOv5 detected postures for key tasks, including: installing perimeter taping (IPT), installing plumbed props (IPP), installing supporting beams (ISB), and installing formwork panels (IFP). Results were visualized through Crew Balance Charts, comparing YOLOv5-based and manually constructed analyses. IFP exhibited the best performance results and most of detected images corresponded to Productive Work.

KEYWORDS

Computer vision, productivity, crew balance chart, object detection, AI.

INTRODUCTION

The worldwide construction industry faces a productivity improvement challenge (Mischke et al., 2024). Although this industry represented around 7% of the gross world product between 2000 and 2022, its labor productivity only grew by 10% (Mischke et al., 2024). In contrast, the global total economy´s labor productivity grew by 50% during the same period and it almost doubled in Manufacturing (Mischke et al., 2024). The construction industry in Chile follows a similar pattern, accounting for 6.5% of the gross domestic product (Solminihac, 2017), with limited improvements in productivity. Moreover, between 2000 and 2018, labor productivity in the Chilean economy increased by 20%, whereas the construction industry's productivity remained almost unchanged (CChC, 2020).

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Experts and industry leaders in benchmark economies consistently identify technology as a critical driver for productivity improvement in the construction sector (CChC, 2020; Kedir et al., 2020). Therefore, adopting technologies and methodologies can leverage the construction industry's productivity while reducing rework and optimizing supply chain and resource utilization (Kedir et al., 2020). However, since construction productivity challenges are multifaceted and arise throughout the value chain, productivity measurement on construction sites is often subjective, time-consuming, and labor-intensive (Dixit et al., 2019). This research focuses on supporting productivity measurement in construction sites by implementing AI-assisted object detection technology with Lean principles and approaches. In the next paragraphs we briefly review some lean principles related to productivity and how we measure it today and current approaches for AI-assisted estimations.

LEAN PRINCIPLES FOR PRODUCTIVITY MEASUREMENT

Lean principles, proposed by Ohno in 1988, aim to identify and eliminate waste in processes (Ohno, 1988). From the Lean perspective, waste does not add value to the customers. Thus, only operational processes that satisfy customers' requirements must be performed (Shou et al., 2020). Lean literature defines three types of activities: Value-adding activities (VA), Non-value-adding activities (NVA), and Necessary Non-value-adding activities (NNVA) (Shou et al., 2020). In the literature, more than a hundred lean methodologies are available to identify and eliminate NVAs that do not add value to customers, where Value Stream Mapping (VSM) is the most studied among researchers (Jasti & Kodali, 2015). The VSM illustrates the flow of activities involved in delivering a product, distinguishing between value-adding activities, such as direct progress, and non-value-adding activities, including delays, unnecessary movement, and rework (Rosenbaum et al., 2014; Pasqualini and Zawislak, 2005; Yu et al., 2009). This lean methodology helps practitioners identify and eliminate processes' inefficiencies to enhance process performance.

CURRENT PRACTICE FOR PRODUCTIVITY MEASUREMENT

Nonetheless, measuring process productivity requires distinguishing between productive and contributory work times for informed decision-making to optimize resources and time. The Crew Balance Chart (CBC) is a methodology designed to collect and report the distribution of working times of each worker within a group activity by classifying tasks into three categories: Productive Work (PW), Contributory Work (CW), and Non-Contributory Work (NCW) (Oglesby et al., 1989). PW refers to tasks that add value to the final product and are critical for project progress. CW encompasses essential tasks for supporting activity progress, although they do not add direct value. NCW includes tasks that neither add value nor support progress and may introduce delays to the activity. Under the lean perspective, PW represents VA, CW represents NNVA, and NCW conveys NNVA. The CBC classification helps analyze productivity and identify areas for improvement, but it requires onsite data collection. Lin et al. (2021) points out that CBC is used in the industry to study construction activities, and they proposed a line chart (based on CBC) for construction equipment productivity measurement.

AI-ASSISTED PRODUCTIVITY MEASUREMENT

Several industries, including construction, implement artificial intelligence (AI) algorithms for hazard monitoring and personal protective equipment detection while collecting historical data for future projects (Pampliega, 2019). These AI algorithms can support human decision-making by collecting, analyzing, and optimizing data, images, and videos. Among these AI algorithms is the YOLOv5 algorithm, a Machine learning-based algorithm known for its real-time object detection capabilities in images or videos (Jocher et al., 2020). The object detection confidence of the YOLOv5 algorithm relies on training the AI with target objects and the mean average precision (mAP) metric. This mAP supports refining the model during training for better performance, and previous research identified successful outcomes when mAP is greater than 65% (Nelson, 2020). Some authors have tried to measure construction workers activities using vision-based techniques and machine learning. Jacobsen et al. (2023) proposed using deep learning techniques and kinematic sensors on construction workers for measuring the type of work they perform (direct, indirect and waste). Alwasel et al. (2017) tested a vision based method for measuring construction worker pose on site conditions, but it required a full IMU-based motion capture suit. Alsakka et al. (2023) proposed a vision-based approach for measuring start time, productive time and cycle time on offsite construction. Cheng et al. (2023) proposed using a YOWO algorithm (based on convolutional neural networks or CNN) for identifying workers activities on construction sites, but their focus is on worker´s detection and not on activity productivity measurement directly.

This research aims to evaluate worker performance and productivity by integrating Value Stream Mapping (VSM) with AI-assisted Crew Balance Charts (CBC) using the YOLOv5 algorithm. The approach leverages onsite video and image data, employing artificial intelligence to generate CBCs more efficiently than traditional manual observation methods. Our research builds on previous studies, such as Mora's (2009) study, which explored developing Crew Balance Charts with technology assistance. Additionally, the research team developed a body-task taxonomy to categorize body postures based on those most commonly observed when performing each task (Salazar, 2020).

The research team developed and tested the proposed methodology based on images and videos of a carpentry crew during the installation of slab formwork. We trained the YOLOv5 algorithm with several pre-identified body postures based on the defined body-task taxonomy associated with PW and CW. This study aims to develop an AI-assisted approach that supports analyzing and reporting crew time distribution during onsite activities. The study aims to reduce Crew Balance Chart development time while leveraging onsite managers' decision-making toward productivity.

METHODOLOGY

In this study, we created a simplified VSM of the concrete slab construction process, and we specifically focused on the slab formwork installation as the critical activity. We then defined a taxonomy with the body postures of the workers for each of the tasks of the selected activity. We recorded videos using a GoPro Hero5 camera (4K @ 90 fps) (GoPro, 2016) around the workforce to capture several perspectives of the workers performing the tasks. We referred to them as “360-degree” videos because they record the workers from the front, back, and both sides during the performance of their tasks. We then used images extracted from these videos to train the YOLOv5 algorithm to detect body postures associated with Productive Work (PW) and Contributory Work (CW).

After the initial training, we recorded the slab formwork installation activity with a fixed camera. The YOLOv5 algorithm processed the images to detect body postures and generated Crew Balance Charts for each task. Then, we compared the AI-generated Crew Balance Charts with manually created ones to evaluate the algorithm's accuracy in detecting body postures and measuring workers' task durations. This analysis supports task supervision and monitoring, contributing to productivity improvement. We schematically explain the research tasks in Figure 1 and briefly describe them next: (i) Through the use of a VSM, we identified formwork installation as a critical activity in the construction of reinforced concrete slabs due to its extended duration. Through this analysis, (ii) we established a preliminary taxonomy of workers' body postures, classifying tasks to distinguish between Productive and Contributory Work. The Taxonomy includes the workers body posture; and the tools and materials used for the activity completion; (iii) Following a comprehensive field observation, we refined the Taxonomy by adjusting tasks, body postures, tools, and materials associated with slab formwork installation, establishing the final taxonomy version. (iv) We recorded 360-degree videos at ground level to capture workers from all perspectives. We extracted images at 5-second intervals using the GoPro Quik App (GoPro, n.d.), labeled them according to the body posture taxonomy using LabelImg (Tzutalin, 2015), and used them to train the YOLOv5 algorithm. 1,500 images were analyzed, with mean Average Precision (mAP) to assess the training performance for each task. (v) The entire activity was recorded using the same GoPro camera, positioned at a fixed location, to facilitate the measurement of productivity during the monitored task. Then, we extracted images using GoPro Quik App every 5 seconds and processed them with the YOLOv5 algorithm to detect body postures for each task. The resulting Crew Balance Charts, generated with the assistance of YOLOv5, were compared to manually constructed charts developed using the same sampled images, but classified by the researchers according to the defined taxonomy; (vi) We developed a methodology proposal based on insights from the case study on productivity measurement for a work crew using video analysis and image detection with the YOLOv5 Machine Learning algorithm.

CASE STUDY

Our research was conducted in a reinforced concrete residential building in the San Joaquín district of Santiago, Chile. The 16-story structure comprises 14 apartments per floor, with a total area of 7,467 m². The project was developed by a real estate company specializing in mid and high-rise buildings in Chile.

A construction process (e.g., construction of reinforced concrete slabs) is divided into multiple activities (e.g., installation of formwork, installation of rebar, etc.), which are further broken down into individual tasks (e.g., installing perimeter taping, installing plumbed props, etc.). The VSM identified slab formwork installation as the most critical activity during the preliminary construction stage. A six-member carpentry crew, including four carpenters and two assistants, performed this task. The carpenters were responsible for installing perimeter taping (IPT), installing plumbed props (IPP), installing supporting beams (ISB), and installing formwork panels (IFP), while the assistants supported material transport and formwork removal. Figure 2 illustrates the building's features, workers' field conditions, body postures, and the tools and materials used in the tasks.

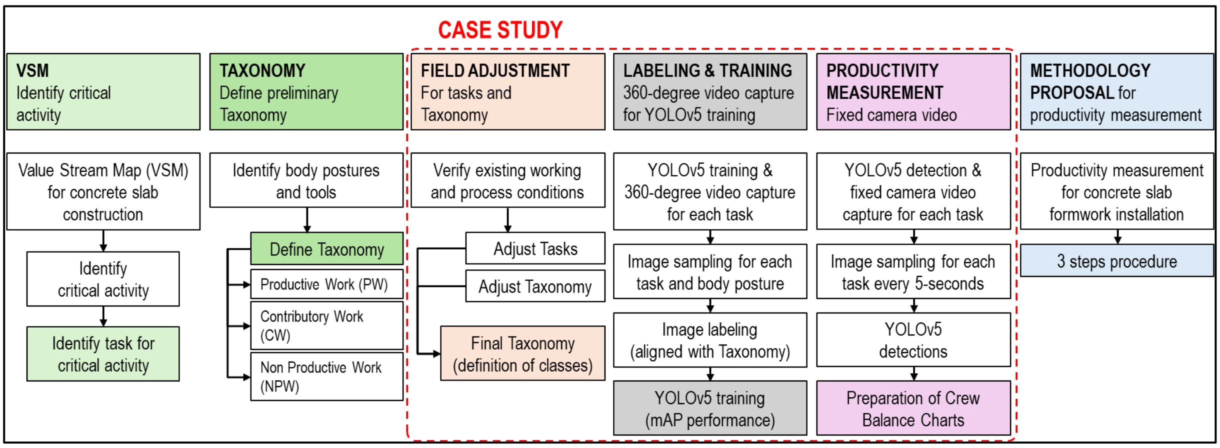

Figure 1: Research Methodology.

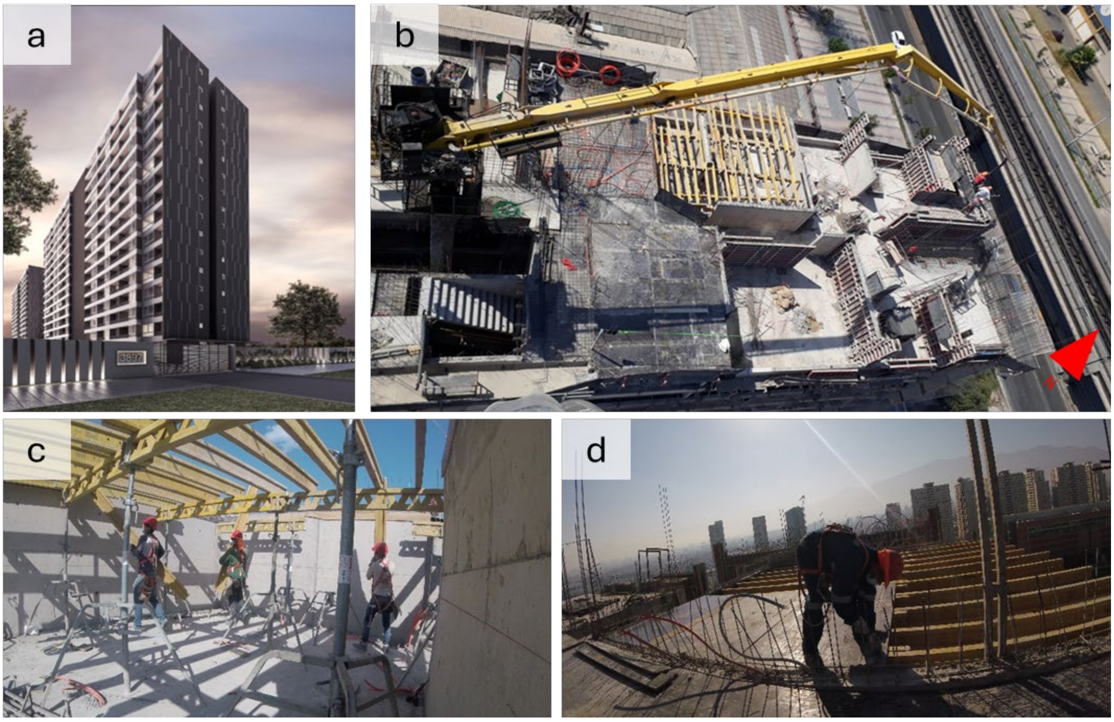

Figure 2: Case Study. (a) Building North Façade (render); (b) Plant view during reinforced concrete rough works; (c) Workers installing slab formwork beams; (d) Workers installing slab formwork panels.

RESULTS

The results of the research are presented in several subsections, including the Value Stream Map (VSM) and the proposed taxonomy of body postures, followed by subsections that describe the video captures used for YOLOv5 training and productivity measurement. Additionally, the Crew Balance Chart for productivity diagnostics and the proposed Methodology are discussed in detail.

VSM & Taxonomy of Body Postures

We developed a simplified VSM of the concrete slab construction process, refining it through field observations of the entire construction process. Our VSM analysis identified slab formwork installation as the critical activity of the concrete slab construction process.

We developed a taxonomy to classify the most representative body postures of the activity, aiming to reduce the number of classes for the algorithm (Salazar, 2020). Within the slab formwork installation activity, we identified four main tasks: 1) installing perimeter taping (IPT), 2) installing plumbed props (IPP), 3) installing supporting beams (ISB), and 4) installing formwork panels (IFP). In Figure 3 we show our Taxonomy of body postures. PW is green, while CW is yellow. We divided the activity into these four tasks, each characterized by its most representative body postures. The body postures identify the worker's tasks and the tools and materials.

Video Capture for YOLOv5 Training

360-degree Video Capture

We recorded 4K videos at 90 frames per second using a GoPro Hero5 camera positioned at ground level, ensuring thorough documentation of the activities. The camera filmed the workers from multiple angles: front, side, and back. The total duration of the footage was 4 hours, comprising 74 videos of varying lengths, depending on the task.

Figure 3: Taxonomy of slab formwork installation. Detail of tasks, body postures, tools, and materials associated with PW and CW.

Labeling

We extracted images from recorded videos at 5-second intervals for labeling, ensuring a balanced number from the worker's front, side, and back using the LabelImg program. As shown in Figure 4, the installation of formwork panels (IFP) includes tasks such as material transport (a), panel positioning (b), and final installation (c). We generated a total of 1,500 labeled images across all tasks and postures: 468 for installation of perimeter taping (IPT), 460 for plumbed props installation (IPP), 324 for supporting beams installation (ISB), and 215 for IFP. We hosted the dataset on the Roboflow platform and divided it into 70% training, 20% validation, and 10% testing sets for use with the YOLOv5 algorithm. For IFP, we used 215 images, labeling 80 as IP01, 35 as IP02, and 100 as IP03.

Training and Performance Metrics

We conducted YOLOv5 training in Google Colab (Google, n.d.), generating a dataset for each concrete slab formwork installation task. For instance, the IFP dataset comprised 215 images, with 151 allocated for training, 42 for validation, and 22 for testing.

Each task underwent 1,000 iterations. The mean average precision (mAP 0.5) for IFP reached 0.996. The remaining tasks exceeded the threshold of mAP 0.65 recommended in the literature, with IPT achieving 0.961, IPP 0.914, and ISB the lowest among all tasks. However, overall performance remained robust, with a combined mAP over 0.85. Figure 5 summarizes the results of the YOLOv5 training, including the number of pictures used, mAP details and convergence.

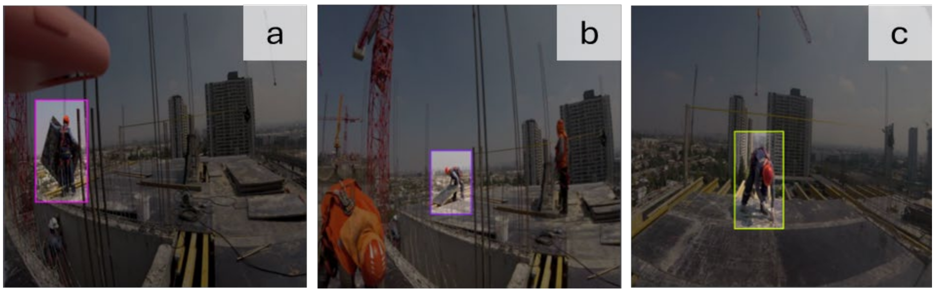

Figure 4: Sample of labeled images for installing formwork panels.

VIDEO CAPTURE FOR PRODUCTIVITY MEASUREMENT

Fixed Camera Video Capture

In contrast to the 360-degree recordings used in the training phase, a fixed GoPro camera was used to document tasks during the productivity measurement stage. The recordings covered the formwork installation of two concrete slabs, with a total recorded duration averaging 44 minutes (42 minutes for slab 1, and 46 minutes for slab 2), resulting in 14 videos and approximately two hours of footage for analysis. The camera was strategically positioned during the installation of perimeter taping (IPT) and plumbed props (IPP) in an upper corner to provide an overhead view of the work area. For the installation of supporting beams (ISB) and formwork panels (IFP), the camera was relocated to capture the work face, as shown in Figure 6.

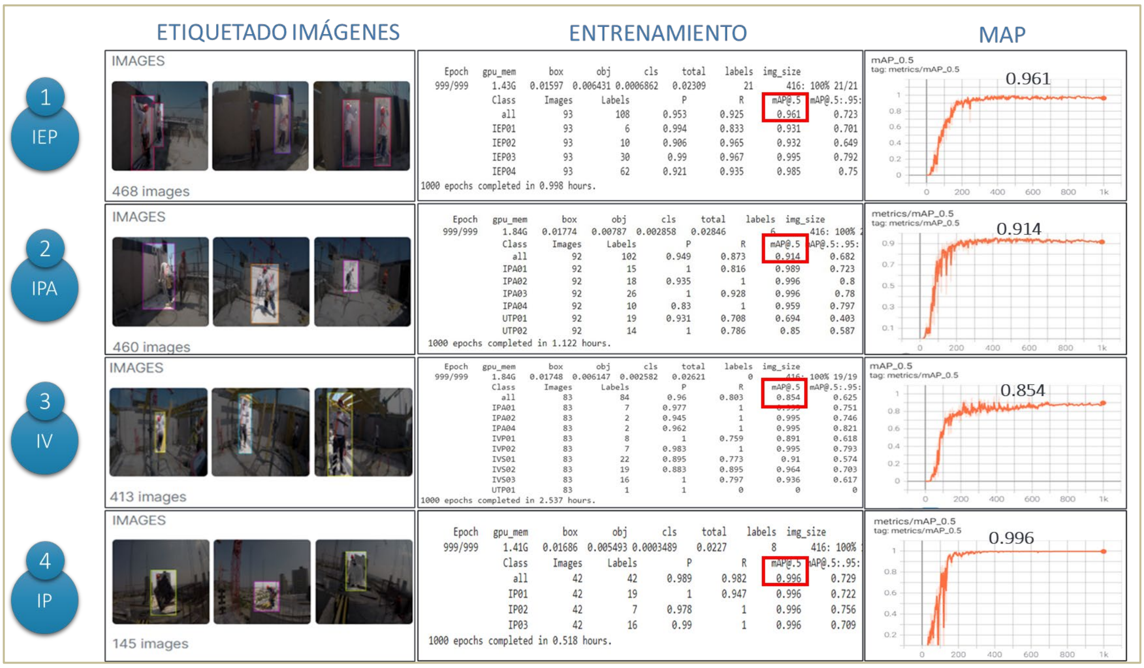

Figure 5: Summary of YOLOv5 training for all activities.

Image Sampling

We extracted images from the recorded videos at 5-second intervals to implement the body posture detection process. For the installation of formwork panels (IFP), image extraction focused on the interval when the task happened (an 8.52-second interval). The research team obtained and analyzed 106 images using the trained algorithm. This study presents the results for the IFP task, which demonstrated the highest performance during the training phase.

Figure 6: Video capture for performance measurement: (a) IPT; (b) IPP; (c) ISB; and (d) IFP.

Task Detection using YOLOv5

We provided 106 images to the YOLOv5 algorithm, trained for the installing formwork panels (IFP) task. As shown in Figure 7, the algorithm achieved a confidence level of 82% in detecting body posture IP03 (a), which corresponds to a worker hammering a panel into position—a task classified as Productive Work (PW). In contrast, the algorithm did not detect body posture IP01 (b), depicting a worker carrying panels and categorized as Contributory Work (CW).

Figure 7: YOLOv5 detection. (a) Productive Work; (b) Contributory Work (no detection).

Crew Balance Charts

After image detection by the algorithm, we generated Crew Balance Charts (CBCs) for all tasks using the YOLOv5 outputs. Figure 8 shows the CBC for the installation of formwork panels (IFP), the task with the highest performance during training and evaluation. The left chart was created manually, and the right chart was generated from YOLOv5 detections, both based on frames extracted every 5 seconds (12 intervals per minute). Since IFP is performed by a single worker, each CBC contains a single bar per interval. From 106 analyzed images, the algorithm correctly detected 59, focusing only on Productive Work (PW, green) and Contributory Work (CW, yellow), excluding Non-Contributory Work (NCW). We validated the detection-based CBC using the manual chart, built from the same image set. Our team used a predefined taxonomy of body postures to classify PW and CW. Postures not included in the taxonomy were labeled as Non-Productive Work (NPW, red), and frames without the worker were labeled as Absent (gray). Thus, accurate detection requires green and yellow bars in the detection-based

CBC to match those in the manual version, and gray and red bars in the manual chart to align with black bars in the detection-based CBC.

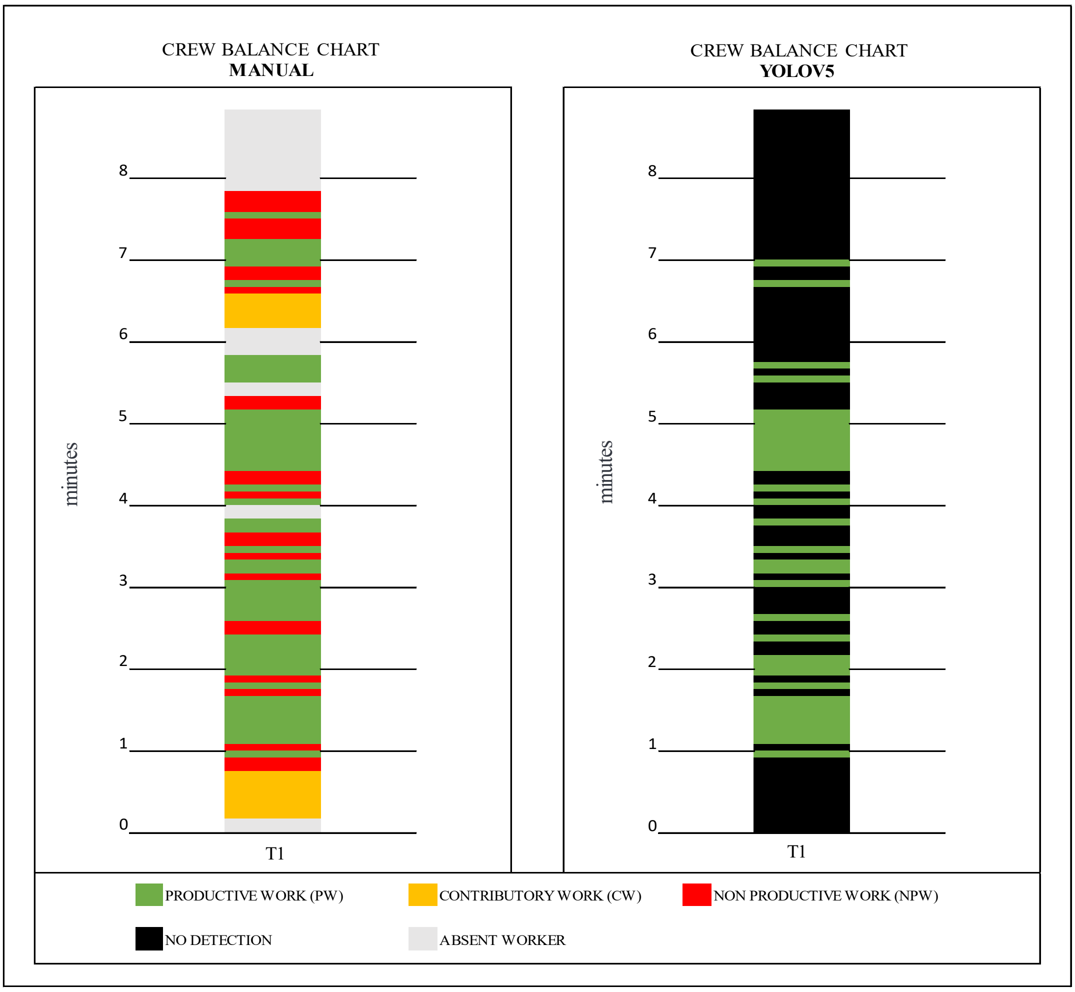

Figure 8: IFP Crew Balance Chart comparison. Sample pictures for 5-second intervals. Left: manually created. Right: YOLOv5 detection-based.

The Crew Balance Chart reflects the algorithm's results, as detailed in Table 1. The algorithm detected 34 out of 47 images associated with Productive Work (PW), achieving a 72% detection rate. However, it failed to detect any of the 12 images categorized as Contributory Work (CW). Overall, of the 106 images analyzed, 59 corresponded to either PW or CW, with the algorithm correctly identifying 34, yielding a 58% detection rate. Installing perimeter taping (IPT) showed the worst performance. Conversely, installing plumbed props (IPP) and installing supporting beams (ISB) performed satisfactorily.

Table 1: Productivity Measurement from Crew Balance Charts (IFP).

Detection	Manual	YOLOv5	%
Productive Work (PW)	47	34	72
Contributory Work (CW)	12	0	0
Total detections	59	34	58

Methodology Proposal

We propose a methodology derived from insights gained in the case study, which focused on measuring productivity through video recordings and image detection with the YOLOv5 algorithm. The methodology includes three stages: (1) field adjustment of tasks and taxonomy of body postures, (2) labeling and YOLOv5 training, and (3) productivity measurement.

DISCUSSION & CONCLUSIONS

We analyzed productivity measurement in Chile's construction sector, where low productivity growth underscores the need for innovation. Traditional methods, such as Crew Balance Charts, are limited by subjectivity, time consumption, and labor intensity. To address this, we proposed an automated tool using video capture and body posture detection via the YOLOv5 algorithm to enhance objectivity and efficiency in productivity assessment.

Our methodology focused on installing slab formwork, identified as a critical activity through a VSM analysis. We defined key tasks and classified representative body postures, reducing irrelevant movements to improve classification accuracy. To train the algorithm, we recorded 360-degree videos at ground level, capturing multiple angles of the workforce to enhance detection precision.

The trained algorithm achieved strong performance, with a mean average precision (mAP) exceeding 0.854 for all tasks and reaching 0.996 for installing formwork panels (IFP). However, it failed to detect Contributory Work due to discrepancies between training and productivity measurement images, particularly differences in lighting conditions, differences in camera angles (360-degree videos vs fixed camera videos), occlusions, and scene background objects. Therefore, ensuring consistency in image conditions between training and measurement stages is crucial for reliable detection.

For installing perimeter taping (IPT), obstructions such as props and beams affected detection accuracy. The algorithm struggled to detect a key posture (IEP03), as the tape measure was often obscured. While YOLOv5 effectively identified Productive Work, Contributory Work detection remained suboptimal, aligning with the discrepancies observed in manual Crew Balance Charts. Our findings highlight the need for controlled image conditions and refined training datasets to optimize automated productivity measurement in construction. However, we consider this proof of concept to be a valuable starting point, although further refinement is needed, particularly in the classification of Contributory Work (CW) tasks.

FUTURE WORK

We propose applying this methodology to other rough work and finishing activities in construction. For optimal body posture detection, recordings should use multiple fixed cameras to ensure comprehensive footage coverage of the workforce from various angles.

Additionally, we recommend using YOLOv5 for real-time detection of material movement and body postures, enhancing precision and detail for CW, as it was not detected in our case study. In future work, we aim to automate the generation of Crew Balance Charts by leveraging the results from YOLOv5, thereby eliminating the need for manual processing. This approach will contribute to advancing the construction industry towards the goals of Construction 5.0, enhancing efficiency and minimizing human error with the use of AI and machine learning.

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