Peinado, H.S., Melo, R.R.S., Santos, M.C.F. & Costa, D.B. (2023). Potential application of deep learning and UAS for guardrail safety inspection. *Proceedings of the31st Annual Conference of the International Group for Lean Construction (IGLC31),* 387–398. doi.org/10.24928/2023/0148

POTENTIAL APPLICATION OF DEEP LEARNING AND UAS FOR GUARDRAIL SAFETY INSPECTION

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ABSTRACT

Unmanned Aerial Systems (UAS) can provide valuable information about on-site compliance with safety regulations, especially identifying workers in areas without guardrails or fall arrest systems. Despite the advances in using Machine Learning (ML) and, more specifically, Deep Learning (DL) algorithms for detecting safety systems in construction, the literature indicates a gap regarding automatic guardrail recognition. Therefore, this paper proposes a set of criteria for data collecting and processing using UAS and DL for safety inspections in temporary guardrails while producing cast-in-place concrete wall systems. For this research, an exploratory case study was adopted as the research strategy, developed according to the following steps: (a) database image analysis, (b) field study on constructions, (c) formal meetings, and (d) survey carried out with ML/DL specialists. Results show the main failures in guardrails of cast-in-place concrete wall systems, analyzing which can be inspected using UAS visual assets and ML/DL techniques. Also, it indicates the more adequate construction stages to perform safety inspections on guardrails. These findings may guide future research using UAS and DL algorithms for inspecting guardrail safety systems to further contribute to managers' decision-making.

KEYWORDS

Drone, Machine Learning, Construction 4.0, Safety management, case study.

INTRODUCTION

Fall from height (FFH) is one of the main types of accidents in the construction industry (Fang et al., 2018a; Nadhim et al., 2016; Zermane et al., 2023). To avoid FFH-related accidents, a commonly adopted control measure in the Brazilian context (Brasil, 2020; Peinado, 2019) and international context (Baruffi et al., 2021) are collective fall protection systems, such as guardrails. The guardrail system limits workers' movement, preventing them from reaching the area with FFH risks. Despite this, in the 114 FFH accidents analyzed by Zlatar et al. (2019), missing or inadequate guardrails contributed to 65.8% of the cases, positioning this failed measure as the second leading cause, only after the procedure of work, presented in 81.6% of the cases. Nadhim et al. (2016) also highlighted that inadequate guardrail systems are among the main factors that cause FFH accidents in construction.

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Poor safety is considered waste in the context of Lean Construction (Nahmens & Ikuma, 2009). Waste in production is understood by Ohno (1988) as all activities that add cost but not value. Accidents and injuries are costly in terms of human suffering and affect the level of worker satisfaction and the general well-being of the population. However, they are also financially onerous regarding worker compensation costs, lost time, lost productivity, higher employee turnover, and worker retraining (Nahmens & Ikuma, 2009; Peinado, 2019). During construction activities, monitoring workers and the construction site environment can prevent accidents (Carter & Smith, 2006). Safety monitoring is a critical element of safety management, but this activity is often performed inefficiently. Without adequate technological support, monitoring the entire site becomes an impractical task, given the size and dynamic character of the site (Golparvar-Fard et al., 2009; Guo et al., 2017).

The use of unmanned aerial systems (UAS) (also known as drones) can provide information to improve the safety conditions in construction sites (Costa et al., 2023). The use of UAS to help identify potential risk sites and for safety inspections in building construction has been validated over the last years by the scientific literature, placing it as an essential tool in the context of Construction 4.0 (Rachmawati & Kim, 2022; Costa et al., 2023). Using UAS results in the collection of visual assets allows better visualization of working conditions and, therefore, enhances the improvement of safety inspections at construction sites (Martinez et al., 2020; Melo et al., 2017; Rey et al., 2021).

Considering the large volume of data generated in construction (Baduge et al., 2022) and the limited number of safety professionals on construction site (Kolar et al., 2018), computer vision has been applied to support safety inspections (Akinosho et al., 2020; Pham et al., 2021; Ottoni et al., 2022). According to Baduge et al. (2022), Machine Learning (ML) and Deep Learning (DL) algorithms have been extensively used in the construction industry, addressed to architecture, materials, structures, construction management, progress monitoring, and work safety, among other areas.

The number of publications on work safety in construction applying ML and, more specifically, DL techniques in the computer vision context for detecting safety equipment and systems has increased in recent years (Akinosho et al., 2020; Pham et al., 2021; Ottoni et al., 2022). The papers refer to the automatic detection of personal protective equipment (PPE) (safety belts, hard hats, safety glasses, and vests) and collective protection systems, detection of machines, ergonomics, and positioning of workers, among others (Akinosho et al., 2020; Pham et al., 2021; Ottoni et al., 2022). Kolar et al. (2018) worked on a detection model for guardrail systems. For the training phase of the model, Kolar et al. (2018) used synthetic images resulting from placing the 3D guardrail (developed in Autodesk Revit) in images from the construction environment obtained from Google. The researchers used a dataset with real construction site guardrails images for model validation. Some specifications to be considered in this research: a) Only images from conventional cameras were used for the validation phase, not applying images from UAS cameras, for example; b) only synthetic images were considered for training, assuming that the guardrail will always be visible and without obstructions that compromise its correct visualization, which does not represent the reality of construction sites; c) only one guardrail model was analyzed without further details about the standard supporting its configuration or which construction stages this system is used. Recently, Li et al. (2022) worked on a framework for using UAS and ML to monitor fall hazard prevention systems, such as guardrails. Despite the efforts, the paper focused only on detecting guardrail posts, not considering the entire safety system.

Therefore, this paper proposes a set of criteria for data collecting and processing using UAS and DL for safety inspections in temporary guardrails while producing cast-in-place concrete wall systems. These findings may guide future research regarding using UAS and DL algorithms for inspecting guardrail systems in construction, providing potential problems to be identified, and possible DL techniques for problem automated detection. The primary purpose of pursuing this research field is to support identifying safety systems failures more efficiently and contribute to managers' timely decision-making.

LITERATURA REVIEW

UAS FOR SAFETY APPLICATION

Irizarry and Costa (2016), Costa et al. (2016), and Gheisari and Esmaelli (2019) explored the UAS's potential to inspect safety conditions. The results showed some safety issues, such as inadequate or missing safety guardrails, damaged safety nets, and inadequate scaffoldings. Melo et al. (2017) conducted two case studies at construction sites to assess the UAS applicability to performing a safety inspection, using the visual assets to check the compliance of safety items. The results show that the UAS can provide valuable information about on-site compliance with safety regulations, especially identifying workers in areas without guardrail systems or fall arrest systems. Lima et al. (2021) implemented UAS safety monitoring in a construction site to improve safety planning and control (SPC). The results present that the visual assets collected using UAS could be used to plan preventive and corrective actions, improve the collaboration between the safety and production teams, and increase the transparency of safety conditions.

Through a case study, Martinez et al. (2020) proved that the UAS can support hazard identification and assessment, especially those associated with height conditions, such as missing guardrails and safety nets around unprotected edges, floor openings, and loose or unsecured material at height.

Gheisari and Esmaelli (2018) proposed a workflow using point cloud data generated by UAS to detect the location of the guardrail and openings and then check if they are safety-approved. As a result, they located in a 3D mesh the position of the opening. Mendes et al. (2018) carried out a testbed to evaluate the feasibility of automatic recognition of normative requirements related to guardrails using UAS visual assets. The findings showed that only parametrizable conditions could be inspected through images, lowering the reliability of the algorithm tested (errors close to 20%).

Thus, the literature generally indicates a gap regarding the automatic guardrail recognition integrated with management routines to promote timely decision-making (Mendes et al., 2018; Gheisari & Esmaelli, 2018). According to those authors, the different types of guardrails (color, shape, materials, and geometric properties) are one of the main barriers to automating this process.

DEEP LEARNING FOR SAFETY APPLICATIONS IN CONSTRUCTION

ML algorithms become challenging when working with high-dimension data (Pham et al., 2021). According to the authors, DL algorithms outperformed ML algorithms in safety research once they deal with high-dimensional input data. When equipped with convolutional layers, the DL algorithms become highly efficient in resolving the issue of data sources (e.g., images and videos) (Pham et al., 2021).

Even though the DL has the potential to automate the identification of hazards on construction sites, a fully automatic computer vision-based system still needs to be developed (Fang et al., 2020). Thus, the primary DL technique's challenge is selecting a structure that ensures good performance metrics, such as accuracy and precision (Ottoni et al., 2022), and the fusion of data (e.g., text) with image/video to better understand the nature of the problem (Fang et al., 2020).

Some studies have used DL to monitor safety behavior and identify unsafe conditions on construction sites, especially falling protective equipment (Fang et al., 2018b; Fang et al., 2020;

Guo et al., 2020). Kolar et al. (2018) developed a detection model to inspect guardrails by analyzing 2D images captured from construction sites. According to these authors, DL is a promising construction site safety monitoring approach.

However, despite the diverse DL techniques presented in the studies, there is still a gap in testing new solutions to achieve even higher accuracy and fewer false positives for guardrails detection (Kolar et al., 2018).

RESEARCH METHOD

The strategy adopted was an exploratory case study. According to Yin (2018), this strategy aims to identify procedures to apply in future research. The activities performed in this research are illustrated in Figure 1. The following sections describe these steps in more detail.

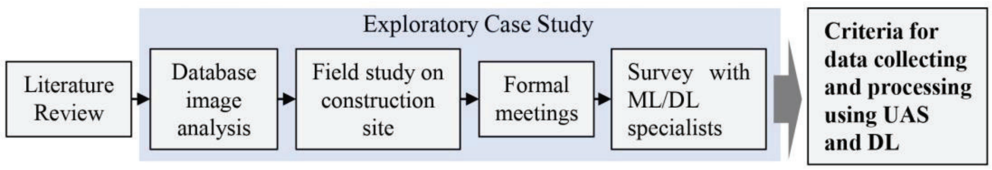

Figure 1: Research Design

CHARACTERIZATION OF THE SAFETY SYSTEMS

In the Brazilian context, guardrail systems are regulated by NR-18 (Brasil, 2020). According to this regulation, the guardrail system can be a solution adopted to prevent workers from falling from height and help avoid the projection of materials in the edge and openings in slabs. If adopted, the system must fulfill measurement, dimension, and load support requirements, among others.

As the formwork system is industrialized, the construction industry has adopted temporary metallic guardrail systems for cast-in-place concrete wall systems. In general, there are two safety systems in this type of construction using guardrails (Figure 2):

The temporary guardrail at the edge of the slab and in the contour of openings in the work area. This system comprises metallic guardrail panels 120 cm minimum high with a toe board supported on the surface (15 cm tall) and guardrail posts fixed on the formwork;

The temporary work platform with guardrails, allowing workers to perform their activities around the story under construction. This system is also fixed on the formwork. The components are work platform consoles, metallic board (floor), metallic guardrail panels with toe board (attending the minimum specifications of the system), and guardrail posts.

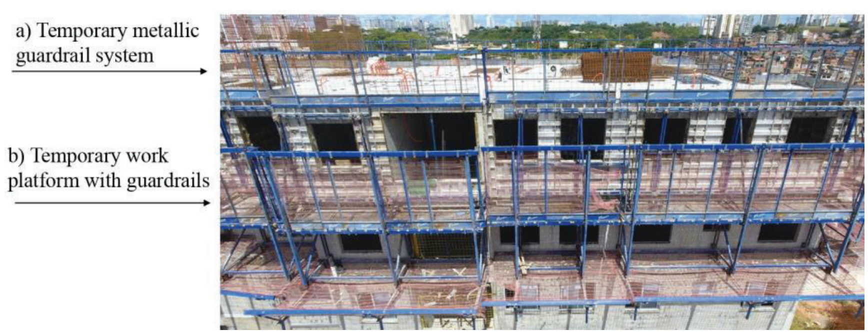

Figure 2: Safety Systems with Guardrails in the Construction Site

DATABASE IMAGE ANALYSIS

Ninety images of building construction sites captured using a UAS were selected to identify safety problems in guardrail systems and temporary work platforms. The items specified were considered a problem if they could compromise the correct functioning of these safety systems. These images were obtained from the Research Group database of which the researchers are part. This database has pictures collected using UAS from 9 construction sites. The analysis of the images to create the categories of problems and, subsequently, to identify these problems in each of the photos was carried out by three specialists in Occupational Safety Engineering (OSE) (the first three authors of this paper). The characterization of the OSE is as follows: 1) Civil Engineer, M.Eng., PhD student – 12 years of experience in the construction industry – 3 years of experience in inspections with UAS; 2) Civil Engineer, M.Eng., PhD, Postdoctoral researcher – 8 years – 8 years, respectively; 3) Civil Engineer, M.Eng., PhD student – 6 years – No experience with inspections using UAS, respectively. At least two OSE specialists analyzed each image to ensure that all problems were identified on the images.

FIELD STUDY ON CONSTRUCTION SITE

This stage aimed to identify the production activities of cast-in-place concrete wall structures, including installing and removing safety systems. Two visits were made to the construction site for direct observation of the process and an interview with the engineer responsible for the construction project. The unit case consists of the construction of four buildings in cast-in-place concrete walls of ten floors each, carried out in northeast Brazil. The stages in which the safety systems are installed were identified to determine when UAS flights could contribute to the safety inspection of these systems.

FORMAL MEETINGS AND SURVEY

Formal meetings and a survey were performed to discuss how UAS and ML/DL techniques could work together for safety inspections of guardrails in construction to investigate possible ML/DL techniques to explore these problems and how to standardize the collection of images for better data processing. Five meetings were held, lasting 1 hour and 30 minutes each, with the researchers (OSE) and three ML/DL specialists (ML/DLs). The characterization of the ML/DLs is as follows: 1) Electrical engineer, M.Eng., PhD, Professor, and Researcher – 13 years of experience in the AI area – 3 years of experience specifically in ML/DL-based computer vision; 2) Telecommunications engineer, M.Eng., PhD, Professor, and Researcher – 10 years of experience – 3 years of experience; 3) Electrical engineer, M.Eng., PhD student – 3 years of experience – 2 years of experience.

The survey was carried out with the same three ML/DLs, for each problem type identified in the database image activity. Based on their experience, they were questioned about: 1) The potential for automatically identifying the problems from stage 1 using ML/DL algorithms; 2) What contributes to or limits a problem from being automatically identified by ML/DL algorithms; 3)What ML/DL techniques they suggest for the automated identification of these problems from images collected using UAS; 4) What is the angle of the UAS camera (camera tilt) that they believe to be the most suitable for collecting these images at the construction site (0°, 20°, 30°, 45° or 90° to the horizontal), for further processing by ML/DL algorithms.

To answer the first question, a 5-point Likert scale was used, labeled from 1 to 5, as follows: 1) There is no potential; 2) There is little potential; 3) Not sure; 4) There is a great potential; 5) I am sure ML/DL techniques will identify the problem. The result from question a) was also presented in colors: 1 presented in red, 2 in grey, 3 in yellow, 4 in green, and 5 in blue. The questionnaire was elaborated in Google Forms. Several images were used to represent the problems to be analyzed, and images were collected at construction sites with different angles of the UAS camera.

Based on the previous outputs, the systematization of the results, analyses, and discussions were performed to propose a set of criteria to support safety inspections on construction guardrails using UAS and ML/DL techniques.

RESULTS

Types of Problems Identified at the Safety Systems

Based on the analysis of the 90 images from the database by the safety specialists, ten types of safety problems related to temporary guardrails and temporary work platforms with guardrails were identified. The issues and the number of images in which each issue appears are shown in Figure 3.

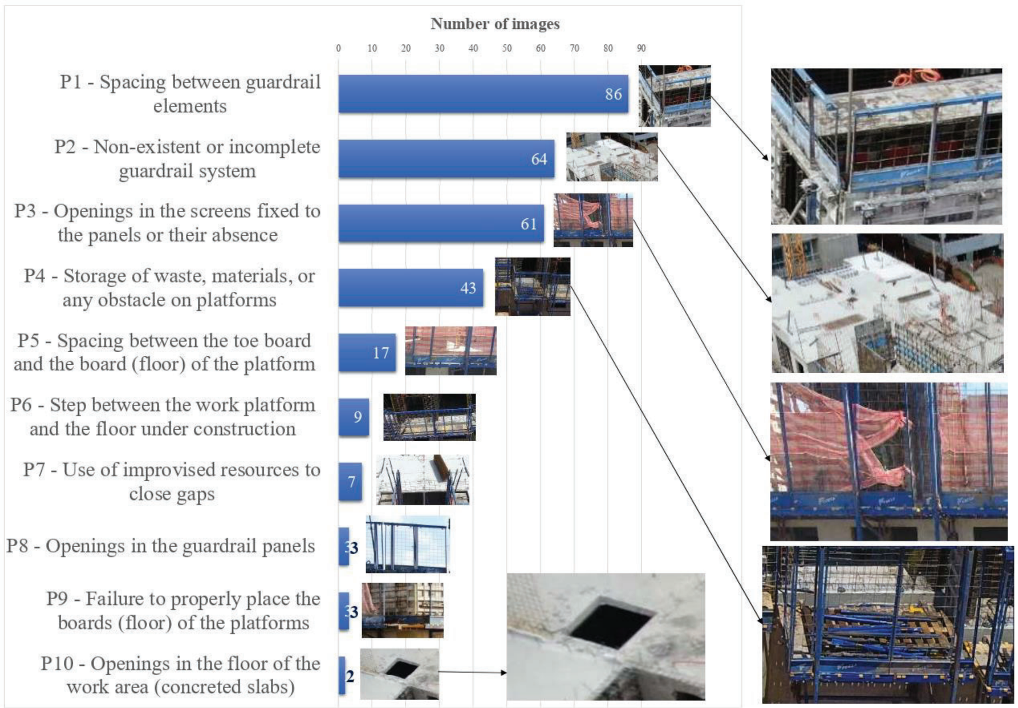

Figure 3: Types of Problems in Temporary Guardrail Systems and Work Platforms

According to Figure 3, problem P1 (spacing between guardrail elements) was identified in 95.5% of the images, while P2 (non-existent or incomplete guardrail system), P3 (openings in the screens fixed to the panels or their absence), and P4 (storage of waste, materials, or any obstacle on platforms) were identified in 71.1%, 67.8%, and 47.8% of the images, respectively. Problems P5 to P10 were identified in less than 20% of the photos.

Construction Sequence tor the Cast-In-Place Concrete Wall System Analyzed

The sequencing of activities related to the production of the cast-in-place concrete wall system of the unit case is presented in Figure 4. The execution of the structure of each floor occurred in two stages, with side A and side B being built at different times. The company had only a set of formwork (for half of the story). Thus, after concreting the walls on side A and the concrete reached the required design strength (generally around 12 hours), the formwork was removed from side A and positioned on side B. Side B should already have the wall reinforcements, electrical, and plumbing ready to receive the formwork of the walls and continue the activities. When the forms on side B were removed (after the concrete had hardened), they were taken to the continuity of activities on side A of the upper floor.

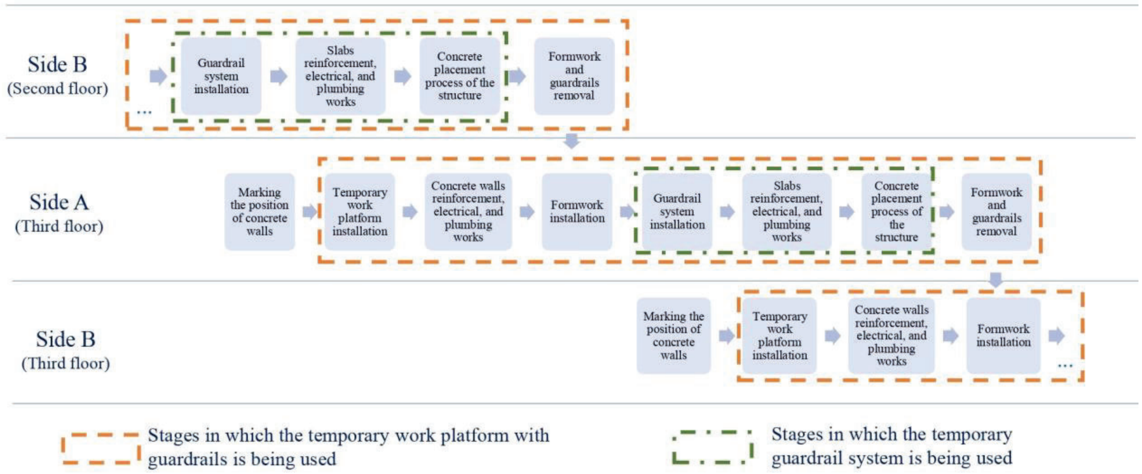

Figure 4: Production Activities of the Structure

Figure 4 shows the activities that integrate the executive sequencing adopted for building each side of the story in the analyzed site. This sequencing was applied from the construction of the second floor to the top floor, in which the installation of the temporary work platform with guardrails became essential. In Figure 4, it is also possible to observe which safety systems were used or were available for use during the execution of each of the activities.

In the process adopted at this construction site, it is observed that only during the activity of marking the position of concrete walls is there no guardrail system or temporary work platforms with guardrails on this side of the construction floor. Lifeline systems were implemented in the construction area for the workers' safety in this activity.

Potential Problems to Be Analyzed by ML/DL Algorithms

The ML/DL Specialists' perception of the potential for automated detection by ML/DL algorithms of the ten problems identified in guardrail systems or temporary work platforms with guardrails from images collected with UAS is presented in Table 1.

Table 1: Potential for Automatically Identifying the Problems by ML/DL Algorithms

Problem	ML/DLs 1	ML/DLs 2	ML/DLs 3
P1	4	4	5
P2	4	4	4
P3	4	3	5
P4	2	2	2
P5	2	2	4
P6	2	2	3
P7	3	2	2
P8	2	3	4
P9	2	3	3
P10	4	4	4

ML/DLs = ML/DL Specialists; 1 = There is no potential (red); 2 = There is little potential (grey); 3 = Not sure (yellow); 4 = There is a great potential (green); 5 = I am sure ML/DL techniques will identify the problem (blue).

Based on the evaluation of the ML/DLs, their perceptions converged regarding problems P1, P2, P4, and P10. Furthermore, there was a convergence of two specialists related to problems P3, P5, P6, and P7.

The problems 'Spacing between guardrail elements' (P1), 'Non-existent or incomplete guardrail system' (P2), 'Openings in the screens fixed to the panels or their absence' (P3), and 'Openings in the floor of the work area (concreted slabs)' (P10) were considered with great potential to be detected by ML/DL algorithms from images collected by UAS. According to ML/DLs 2, problems with the image background cleaner (the most explicit image of the problem) contribute to their identification by ML/DL algorithms. ML/DLs 1 and ML/DLs 2 highlighted that the potential for problem detection by ML/DL algorithms increases when these problems are clear and easily identifiable by a person who is not an expert in the field (in this case, in civil construction). ML/DLs 3 also points out that all situations marked with 4 or 5 present images that fit within a pattern. Thus, it is possible to identify the ideal situation and the situation of the problem. Training the ML/DL algorithm with a significant amount of these images will make it more efficient to detect the problems.

The problems 'Storage of waste, materials, or any obstacle on platforms' (P4), 'Spacing between the toe board and the board (floor) of the platform' (P5), 'Step between the work platform and the floor under construction ' (P6) and 'Use of improvised resources to close gaps' (P7) were considered to have little identification potential by ML/DL algorithms. According to ML/DLs 3, for P4, it will be difficult to train the model only to identify materials on the platform. Thereby, materials on the slabs would also be detected, generating numerous false positives. Furthermore, as highlighted by ML/DLs 2, the excess image information harms identifying materials and residues on the work platform. In this case, the specialist pointed out that the work platform's guardrail will negatively interfere with detecting materials on the platform, as it compromises visual identification. Regarding the problem 'Use of improvised resources to close gaps' (P7), ML/DLs 2 highlighted that 'improvised resources' are unspecific and may involve different types of materials to make the inadequate replacement of the guardrail panels. However, for the correct identification of the problem, an image dataset with a recurrence of this problem is necessary for algorithm training.

Referring to ML/DL techniques recommended by specialists, ML/DLs 3 highlighted that there is no simple solution once the variations among algorithms are subtle, mainly for detection purposes. For this specialist, Faster R-CNN has shown better accuracy for practical tests. At the same time, SSD and R-FCN demonstrate a reasonable balance between accuracy and response time (indicated to be used for real-time applications). ML/DLs 1 e ML/DLs 2 also show CNN algorithms. ML/DLs 1 highlights some techniques for classification (VGG16, Inception, Densenet) and detection (Yolo, SSD).

Regarding the angle of the UAS camera to collect images to use in the training and testing of ML algorithms, the three ML/DL specialists converged on the perception that the camera horizontally (0°) or inclined at 20° to horizontally are the most suitable options since it allows easy visualization of problems classified as high potential (4 or 5). Furthermore, two ML/DLs also indicated the 30° angle as a possibility to be explored. Finally, ML/DLs 2 highlighted the use of a vertical angle for the camera (90° to horizontal), as this angle makes it easier to identify the problem 'Openings in the floor of the work area (concreted slabs)' (P10).

DISCUSSION

Based on the constructive sequence presented in Figure 4, using UAS and ML/DL to inspect temporary work platforms with guardrails should be carried out at any time during the execution of cast-in-place concrete wall systems. This flow of activities indicated that at least one side of the building would have this falling protection system installed and used (Figure 5). Regarding temporary guardrail systems, their use appears in specific stages of the work, meaning their inspections will take place at particular stages of the structure’s production (Figure 4).

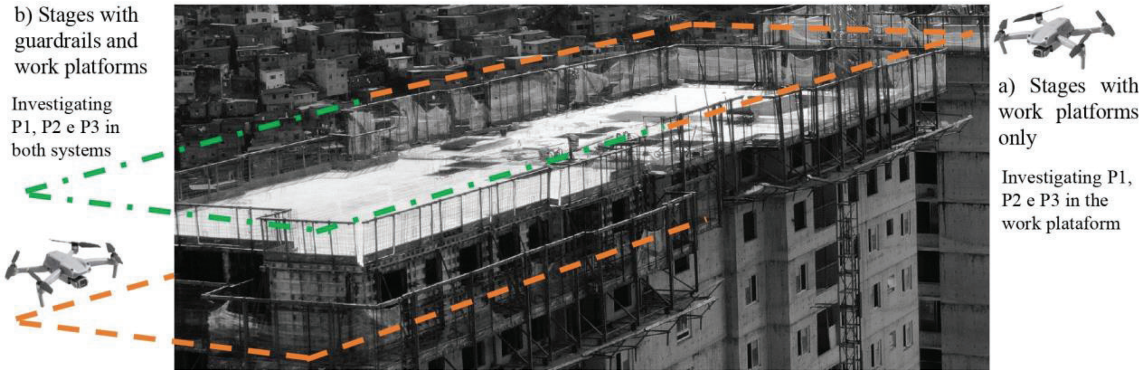

Figure 5: Different Stages for Collecting Data in the Construction Site

This analysis was essential to understand the moments that guardrail inspection should be performed, avoiding unnecessary inspections and consequently reducing non-value-added activities (Womack & Jones, 2003). Thus, the inspection frequency of the safety systems depends on the structure's production rhythm. Therefore, the safety systems should be inspected at a minimum when each story's installation has been concluded.

From the ten problems identified in the falling protection systems used in the cast-in-place concrete wall, problems P1 to P4 appeared more frequently in the images. In contrast, the other problems (P5 to P10) appeared with significantly lower frequency. According to ML/DL specialists' perception of which problems have the most significant potential for automatic detection by ML/DL algorithms, they highlighted: P1 (Spacing between guardrail elements), P2 (Non-existent or incomplete guardrail system), and P3 (Openings in the screens fixed to the panels or their absence). Despite the P10 (Openings in the floor of concreted slabs) being identified by the ML/DL specialists as a problem with great potential to be recognized by ML/DL techniques, it showed low occurrence in the analyzed images. It results in more difficulty using the ML/DL algorithm since there is a need for many images with the referred problem to train it. Thus, this research focused on problems P1 to P3 since they present the most potential to identify using ML/DL and appear more frequently in the images.

Regarding ML/DL techniques, there was a convergence between the recommendations of the ML/DL specialists and the techniques employed and systematized by Pham et al. (2021), Baduge et al. (2022), and, Otonni et al. (2022). Despite the several techniques presented by the ML/DL specialists and in the literature, they mainly focused on using CNN algorithms (a class of DL).

Based on the results and discussion, the set of criteria for data collecting and processing using UAS and DL for safety inspections in temporary guardrails during the production of cast-in-place concrete wall systems is summarized as follows:

The safety inspection with UAS and DL should be performed in some specific stages of the execution of cast-in-place concrete wall systems when the safety systems are already installed;

Ten problems were identified in the safety systems with guardrails. However, only three problems have the potential to be automatically identified by ML/DL algorithms based on the ML/DL specialists' perception and in the occurrence of these problems in the images analyzed, which are: P1 (Spacing between guardrail elements), P2 (Non-existent or incomplete guardrail system), and P3 (Openings in the screens fixed to the panels or their absence);

CNN algorithms (class of DL) should be investigated more for the automated identification of these problems in guardrail systems from images collected using UAS based on the ML/DL specialists' perception and the literature;

UAS cameras should be used horizontally (0°) or inclined at 20° to horizontal for data collecting since it allows easier visualization of guardrail systems' problems for further processing by ML/DL algorithms.

The indicated criteria are important for advancing research involving inspecting guardrail systems using UAS and DL algorithms to further identify these failures with greater efficiency and accuracy. Access to information generated from more agile inspections using UAS and automated detection of problems in guardrail systems (through DL algorithms) may contribute to managers' timely decision-making. This proposition aligns with Principle 8 presented by Liker (2021) regarding technology adoption and adaptation to support people and processes from the organization. In the context of this principle, Liker (2021) highlights that technology has the role of alerting people to problems so they can quickly and creatively respond to them. Based on the experience of Raja Shembekar, Liker (2021) emphasizes that technology provides superior information that enables managers and team leaders to make decisions at a much higher level.

The impacts on visual management are evident once the UAS adds value to the data-collecting process, providing images of the work-in-progress from different perspectives and moving around the construction site more quickly than in conventional situations (Rey et al., 2021; Martinez et al., 2021). In this regard, the UAS combined with ML/DL techniques has the potential to eliminate or reduce the waste of time spent during the inspection, and the safety personnel could be driven to other activities related to workers' involvement and safety culture.

CONCLUSIONS

This research explored the main failures in guardrails of cast-in-place concrete wall systems, analyzing which can be inspected using UAS visual assets and ML/DL techniques. The research has been conducted as an exploratory case study using several sources of evidence, such as questionnaires, database analysis, and direct observation. The results can be generalized to theoretical propositions for similar problems.

The result indicates that four of ten problems (P1 to P4) have the potential to be identified automatically using the ML algorithm. However, this research focus will be on problems P1 to P3 due to the number of images containing the problems. Thus, the discussion defined criteria for data collection using UAS and specified the potential ML/DL techniques used to automatically recognize the guardrails failures during the cast-in-place concrete wall execution. The findings can support the development of a system for automatically detecting safety issues in guardrail systems, which can contribute to managers' decision-making timely related to safety.

Although this research focused on a specific type of guardrail system, this does not mean that ML/DL algorithms could not be applied to other systems. Finally, further studies need to be developed to test ML/DL techniques in this context and propose a method to inspect guardrails using UAS for data collection and an ML/DL algorithm for data processing.

ACKNOWLEDGMENTS

To the Ministry of Education of Brazil through the Coordination for Higher Education Staff Improvement (CAPES) for supporting the scholarship. To the National Council for Scientific and Technological Development (CNPq) for financial support (Project grant number 402380/2021-5). To the MRV Construction Company for financial support.

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