Automating Weekly Construction Activity Progress Reporting: Leveraging AI-Driven Workflows

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Abstract –

This paper presents an automated workflow for weekly construction progress reporting, streamlining data integration and analysis. The proposed approach focuses on three key areas: planned activities, weekly performance, and projected progress. Inputs include an updated baseline schedule and weekly inspection data, such as images. Outputs, generated autonomously, provide project status and performance metrics, including Earned Value and Planned Value. Leveraging multimodal large language models (MLLMs), the system processes text and images, enabling seamless data integration. Key contributions include a simplified, reliable reporting process that reflects actual construction execution and planning while reducing time and resource demands. The paper also addresses implementation challenges, AI-driven solutions, and scalability for broader construction reporting applications.

Keywords –

Construction Progress Reporting, Automation Workflow, Multimodal Large Language Models, Project Management, EVM

1 Introduction

Progress reporting is a cornerstone of effective construction management, offering stakeholders insights into the current status, challenges, and future directions of a project. Weekly reports serve as a critical tool for tracking planned versus actual progress, identifying delays, and updating schedules. However, generating these reports remains a labor-intensive process, often requiring manual consolidation of diverse data sources, including project plans, contracts, on-site observations, and multimedia documentation. Not to mention that such reports are very subjective and based on multiple human-relying factors, such as the quality and completeness of the collected data, the analysis made on said data, and the completion of the actual report.

This paper addresses the challenge of automating construction site progress reporting by designing and implementing a streamlined semi-automated workflow. The proposed system focuses on three core sections of the weekly report:

- Automatically identifying what has been planned for the reporting week;
- Evaluate and determine the activity performance of the reporting week using sight inspection data inputs.
- Update and generate feasible activity plans for the following week.

These sections were selected due to their recurring importance for tracking progress and generating reliable weekly construction status reports.

2 Background

In the construction industry, weekly reports are essential tools for monitoring project progress and ensuring effective communication among stakeholders [1]. A critical component of these reports is the assessment of progress made by construction activity. This evaluation typically involves referencing data from previous reports or updated schedules, while the actual progress for the current reporting week is manually estimated or measured on-site and manually entered into the report. This manual process demands significant time from the engineering team for data synthesis and evaluation, potentially diverting attention from other vital tasks [2].

The quality and accuracy of weekly progress reports heavily depend on the competencies of the individuals preparing them, which can lead to inconsistencies, subjectivity, and biases [3]. The quality of weekly reports is directly linked to the successful coordination between stakeholders and the completion of construction projects. High-quality reports provide early warnings of potential risks and constraints, enabling timely corrective actions.

Automating the generation of construction reports could enhance their quality and accuracy, minimizing subjectivity. By reducing time spent on less productive activities, such as inspection of the collected data and writing the report, automation aligns with lean construction principles, which emphasize waste reduction and value maximization [4]. Within the Last Planner® System (LPS), accurate weekly reports are vital for improving communication and collaboration among all stakeholders involved in the construction process [5]. Weekly plans and reports play a crucial role in identifying and managing construction constraints. They structure constraint information and facilitate the development of data-informed lookahead plans, detailing upcoming work and potential obstacles. This process incorporates actual construction progress into the master schedule, ensuring preparedness for potential issues and adherence to plans [6].

Incorporating automation into report generation not only improves efficiency but also supports the continuous improvement ethos central to lean construction. By streamlining information flow and reducing manual errors, automated reporting systems contribute to more predictable and successful project delivery [7].

2.1 Automated Construction Reporting

As stated above, automated construction reporting have multiple benefits of handling overwhelming data influx from multiple sources and improving productivities. Various studies have proposed workflows aimed at automating the whole construction progress monitoring and reporting system, which consists of four main processes: data collection, data analysis, progress estimation, and visualization [8]. El-Omari and Moselhi [9] implemented automated data acquisition technologies within an IT platform for construction project reporting. Shrestha et al. [10] developed computational algorithms to generate as-built schedules, both during and post-construction, updating progress dynamically. Jafari et al. [11] leveraged Natural Language Processing (NLP) and Machine Learning (ML) for automated reporting extraction, coupled with stochastic simulations to predict time and cost. Xiao et al. [12] integrated computer vision-based data acquisition with ChatGPT to automatically generate construction reports. Shamsollahi et al. [13] created a complete workflow for automated progress monitoring, incorporating object recognition, objectives tracking, and automated report generation. Ekanayake [14] explored computer vision-based progress monitoring, focusing on automated data collection, analysis, and progress report generation.

These advancements underscore the potential of automation in improving the efficiency and accuracy of construction reporting. However, many of them focus on only one or two sub-processes while overlooking manual efforts and the challenges of developing automation tools, which hinders the implementation of a fully integrated workflow.

2.2 Vision-Based Construction Progress Recognition

One of the challenging parts of automated construction reporting is the automated construction progress recognition. The use of images in construction progress monitoring has grown significantly, facilitated by advances in ML [15]. Martinez et al. [16] used an R-CNN model and CCTV footage to track the progress of floor paneling workstations. Wei et al. [17] employed a Mask R-CNN model to track construction activities such as wall construction progress on a single floor. They also used an improved PointRend model to monitor the progress of prefabricated components across an entire building [18]. While these models have demonstrated high accuracy in task-specific scenarios, their effectiveness hinges on high-quality annotated datasets and specialized training. Extensive validation is necessary to ensure these models perform reliably across diverse construction contexts.

In recent days, MLLMs and Vision Language Models (VLMs) have shown tremendous ability to handle text and image information simultaneously in zero-shot tasks transferred to many real-world scenarios [19]. A VLM developed by Tsai [20] for construction safety reporting demonstrated its ability to generate textual descriptions for safety inspectors. Similarly, GPT models, which support few-shot and zero-shot learning can quickly analyze data, adapt to tasks with minimal training, and improve reporting, progress monitoring, and communication, have shown great potential for the construction industry [21]. Pu et al. [22] explored the capabilities of MiniGPT4-7B and GPT-4o in generating automated construction reports, combining automated data collection with LLMs. Despite the aforementioned efforts, the integration of the advanced construction progress recognition methods with the whole automated construction reporting remains underexplored.

In summary, automated construction reporting involves multiple processes, including data acquisition, data extraction, data analysis (e.g., progress description, delay identification, and forecasting), and visualization. While existing research has showcased advancements in automating multi-source data integration and generating construction reports to support decision-making, these efforts often rely on code-intensive workflows and substantial manual input in each sub-process. Vision-based data analysis remains heavily dependent on task-specific datasets and exclusive access to long-term computational resources.

The proposed approach in this paper uses an open-source and expandable workflow automation platform, focusing on seamless and easy integration in current practices and processes. By utilizing a low-code environment and integrating various data processing algorithms, the proposed approach aims to:

1. Simplify and automate progress reporting processes, reducing potential time waste.
2. Eliminate the need for specialized expertise in data collection, processing, and interpretation, by leveraging existing widely used tools for data generation and integration.
3. Minimize bias, reduce manual operations, and enhance workflow efficiency through automation.

3 Methodology

The methodology employed in this study is explained through process flowcharts using the BPMN notation [23]. The overall process is divided into two main sections: (1) manual process (Figure 1) and (2) automated process (Figure 2). BPMN uses "pools" to show the processes of different entities and "lanes" within these pools to present different sub-entities. In this paper, automated and manual processes are presented in separate pools, and different roles involved in the manual process flow are shown in different lanes.

The overall process involves using a developed chatbot to upload site images, and further request weekly progress reports from the chatbot conversation. Telegram was chosen to create the chatbot due to its seamless integration with automation tools. As shown in Figure 1 and Figure 2, a Common Data Environment (CDE) is employed for storing images and schedule files, which serve as the process inputs. While the process reduces manual effort by automating progress reporting, the actual schedule updating remains a separate task and is outside the scope of this paper. This study used Google Drive as the CDE because of its convenience. Overviews of manual and automated parts of the process are presented in the following subsections.

3.1 Manual Process

The manual process involves three roles: (1) site employee, (2) project scheduler, and (3) management/client (Figure 1). The details of each role and related tasks are as follows:

1. **Site employee:** This role is responsible for taking site inspection photos to capture and document the progress. It can be anyone who works on-site and has access to the developed chatbot. The only tasks related to this role are taking site photos and uploading them to the chatbot.
2. **Project scheduler:** This role is responsible for converting the most recently updated MS Project schedule file into the comma-separated values (CSV) format and uploading it to the CDE. CSV was chosen in this study for its structured format, which facilitates data extraction. These tasks and the site employee's tasks are performed in parallel since they are not dependent on each other (Figure 2).
3. **Management/client:** This role represents the stakeholders requesting the report from the automated process flow. Some examples of this role are the site manager, the project manager, and the client. Due to the unbiased nature of the workflow, the generated report provides transparency regarding the project progress and improves the information flow among the stakeholders. The "request report through chatbot" task is dependent on the previous tasks related to photo and schedule uploads performed by the site employee and scheduler.

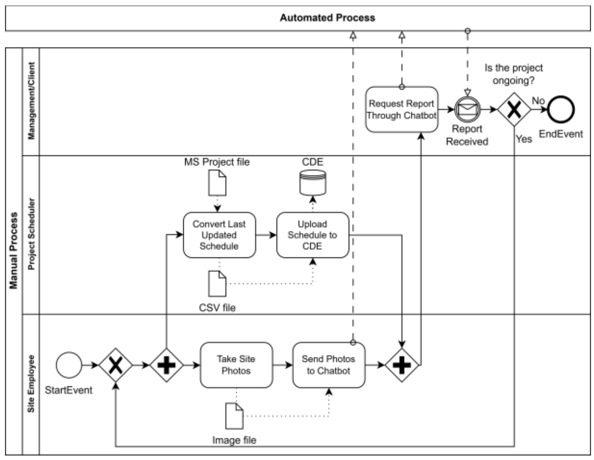

Figure 1. Manual part of the overall process flow

3.2 Automated Process

The automated part of the overall process flow was developed on the low-code workflow automation platform, n8n [24]. This platform was used due to its advanced graphical user interface, which allows visual programming without requiring extensive coding knowledge. However, other low-code development platforms or traditional programming can serve the same purpose.

The automated part of the process flow has two message start events, "photo received" and "report request received", triggered by the tasks from the manual process. Once the site inspection photos are uploaded to the chatbot in the manual process, the "photo received" event is triggered, and the photos are automatically uploaded to the CDE. The connection between the chatbot and the automation process was made using the Telegram node in n8n.

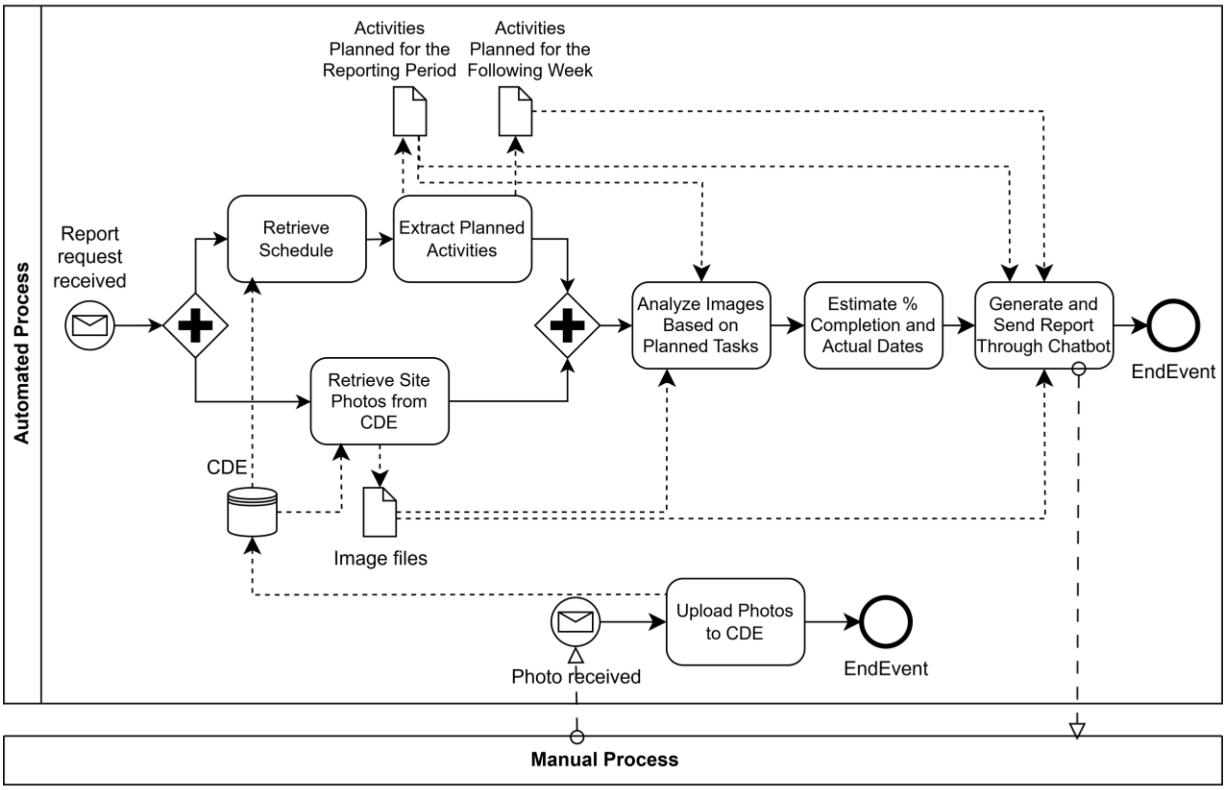

Figure 2. Automated part of the overall process flow

Once the report request is received from the project management or the client, the retrieval of the schedule and photos is performed. These are facilitated through the Google Drive integration of the n8n platform in this study. The activities planned for the reporting period and the upcoming week are extracted from the schedule file using custom JavaScript code and integrated into the n8n workflow via the Code node. The images retrieved from the CDE are analyzed based on the planned tasks using a MLLM. GPT-4o was used in this study due to its powerful capabilities and the built-in OpenAI nodes in n8n. However, an open-source model could be utilized for the same purpose if data privacy or cost were to be prioritized. GPT-4o was used to generate the prompts for its own tasks. This approach ensures structured and efficient prompts for each task.

The MLLM is asked to analyze the construction site images and determine the percent completion of each planned activity, having the rest of the provided information as context for said analysis. The result from this analysis is passed into another LLM instance to compare it with the percent complete values from the last updated schedule, and then output the highest percentages based on this comparison. These percent complete values are then used to calculate the estimated actual start dates for the activities started during the reporting period and the estimated actual finish dates for the activities completed during the reporting period.

Finally, the planned tasks for the reporting period, their percent complete values, the activities planned for the following week, and the site inspection photos are included in the weekly progress report generated as the last step of the automated workflow. The generated report is sent to the user who requested the report through the chatbot.

4 Case-study

This case study presents the automated generation of a weekly construction progress report for a fit-out construction project conducted on a university campus. The project involves the conversion of a meeting venue into an auditorium, incorporating several specialized upgrades to meet the functional and aesthetic requirements of the new space. These upgrades include structural modifications for tiered seating arrangements, enhanced audio-visual systems tailored for auditorium use, and upgrading the heating, ventilation, and air conditioning (HVAC) systems to accommodate the revised space usage. Additionally, the project involves aesthetic and functional enhancements such as floor carpeting and the integration of electrical systems, particularly beneath the stepped seating, to support the operational needs of the auditorium.

The specific week in the timeline used for this case study was selected due to the significant activity observed on-site during that week and the availability of comprehensive data, making it an ideal timeframe for detailed analysis. The focus on this time period captures substantial progress while providing a reliable snapshot of the construction activities. For consistency and accuracy in assessment, the schedule is assumed to be up to date as of the last day of the previous reporting date, reflecting all completed activities up to that point. This assumption ensures a clear baseline for evaluating the progress during this time.

4.1 Data inputs

One of the data inputs necessary for the process was the updated schedule. As of the last day of the previous reporting week, the overall project progress was 54%, with significant milestones achieved. Partition work was 83% complete, with closure and wall finishing still pending. The ceiling installation had reached 37%, with ceiling panel installation not fully completed. Floor preparation tasks were fully completed at 100%. MEP work stands at 38%, with ductwork and data conduit installations finished, wiring and cable installation at 60%, and initial stages of HVAC air diffuser installation underway. The seating area framework and concreting were 63% complete, with framework installation fully finished and rebar installation nearing completion at 90%. The updated list of tasks with their percentage completion is shown in Figure 3. It highlights the project's progress, with several activities scheduled for completion in the target week. The second critical input to the process was raw data from the site inspection. In this case, the site inspection was conducted on the 5th day of the reporting week, and 360 images, such as the one shown in Figure 4, were collected.

4.2 Report generation process

The report generation process is initiated by sending the image taken from the construction site during the inspection directly to the Telegram bot. The Telegram bot initiates the image renaming and uploading process to the cloud data storage space, where the image is renamed to carry the data collection date and stored in the Google Drive folder that is prepared for this purpose.

Custom-made plugins in the scheduling software, Microsoft Projects in this particular case study, were employed to convert the existing schedule to a structured, easily readable data format such as CSV and uploaded to the cloud storage that the workflow can access. As mentioned previously, this case-study experiment employs n8n as the low-code workflow automation platform to connect all the different processes. Hence, a command "/report" in the Telegram bot initiates the relevant information generation process, using the available data inputs that are pre-uploaded in the cloud storage, following the process shown in Figure 1 and Figure 2.

Task Name	% Complete
A6 Room 2 (1B) construction	**54%**
Partition Work	**83%**
Gypsum Board Installation	100%
Closure, finishing wall surfaces	0%
Ceiling Installation	**37%**
Ceiling Frame Installation	100%
Ceiling Panel Installation	10%
Floor preparation	**100%**
Layout and mark the floor for precise positioning of partitions, conduits, seating framework, and other installations.	100%
MEP work	**38%**
Installation of MEP Ductwork and fixture installation	100%
Installation of MEP and Data Conduits	100%
Wiring and Cable Installation	60%
Installation of Wall Fixtures (MEP and Data)	0%
Installation of Floor Boxes (MEP and Data)	0%
Installation of HVAC Air Diffusers and Grilles	7%
Conduct final checks and installation of any remaining electrical components	0%
Seating area framework and concreting	**63%**
Seating Steps Framework Installation	100%
Seating Area Floor Rebar Installation	90%
Concrete casting and covering it with wet curing blanket for seating area	0%

Figure 3. Extract of the Baseline tasks list and percentage completion updated as of the last day of the previous reporting week.

Figure 4. 360 image taken during the site inspection on the 5th day of the reporting week

5 Results

The generated report is composed of five sections, including (1) basic project information, (2) a high-level description of the current weekly site work progress, (3) a summary of weekly project status, (4) a list of tasks planned for next week, and finally (5) a list and descriptions of the inspection photos.

The basic project information section carries the static project information such as Project ID, and designation of the specific zone in the project where the current report is targeted to. This section also provides information regarding the specific reporting week.

The weekly report is meant to be delivered to nontechnical stakeholders, such as clients with limited understanding of the detailed project status metrics. Therefore, the second section provides the list of tasks planned for the current week, dividing these tasks into three different categories: (1) *complete*, mainly for the set of tasks that are finalized during the week; (2) *in progress*, for tasks that are still active but not complete; and the last category (3) *planned but not started yet*, mainly for those tasks that the schedule indicates that they need to be started during the week but have not actually been started in the construction site yet.

For the project used in this case study, even though all of the tasks except ceiling panel installation were planned to be completed by the end of the studied week, the process generated a report showing that none of the tasks were actually completed. Moreover, three of the six planned tasks (i.e., installation of wall fixtures, installation of floor boxes, and concrete work for the seating area) are classified as planned but not started yet in the generated report.

This report offers (Table 1) even more expanded information on the planned vs actual performance of the project showing the Work Breakdown Structure (WBS) ID, Task Name, Status, % Completion to Date (EV), % Planned Completion (PV), and Actual Completion of the work at the end of the reporting week (AC).

Table 1: Output summary of the project status

WBS	Task Name	Status	EV*	PV	AC
1.2.2	Ceiling Panel Installation**	In progress	60%	85%	21%
1.4.3	Wiring and Cable Installation**	In progress	70%	100%	80%
1.4.4	Installation of Wall Fixtures (MEP and Data)**	Not started	0%	100%	0%
1.4.5	Installation of Floor Boxes (MEP and Data)**	Not started	0%	100%	0%
1.4.6	Installation of HVAC Air Diffusers and Grilles**	In progress	50%	100%	90%
1.5.2	Concrete Work for Seating Area**	Not started	0%	100%	100%

* The information was generated from site inspection photos using VLM; hence, verification from the site crew would be required.

** Shows tasks that are potentially delayed according to their SPI value.

Based on the performance of the current week, the automated workflow also presents a section in the report suggesting the list of planned tasks for the next week. This computation considers the SPI of the EVM. Given this case study does not involve the cost calculation, the SPI calculation is summarized as EV/PV, where EV is taken as equivalent to the percentage completion and PV is computed as the ratio of the number of actual activity days related to a planned task with the number of planned days of the task-related activity.

Based on the SPI, the baseline finish date and the revised task duration, the new list of tasks planned for the following week is reported. The last segment of the report presents the raw image data involved in the generation of the report with systematically defined captions that relate the site status and active tasks with the actual image collected. Readers interested in the specific details of the report generated and the data used for the generation of the report are encouraged to contact the authors to request a copy.

6 Discussion

This study successfully demonstrates the potential of automated processes for generating construction weekly progress reports, effectively addressing the three key objectives stated at the beginning of the paper: reducing potential time waste, eliminating the need for specialized expertise in data collection, processing, and interpretation, and lastly minimizing bias in the report results.

The automation demonstrated in this case study reduces potential time waste by streamlining the data collection and reporting processes. Traditionally, generating progress reports involves multiple manual steps, including data collection, image labeling, information synthesizing and processing into a coherent report format. The workflow presented in this study minimizes these repetitive tasks by automating image renaming, cloud storage, data integration, structuring the information into the report, and finally, updating the schedule as per the actual site findings. As a result, site personnel can allocate more time to critical construction activities rather than administrative tasks. This efficiency is particularly valuable in time-sensitive projects where delays in reporting can lead to cascading schedule disruptions.

A significant strength of the approach is its ability to eliminate the dependency on specialized expertise for data collection, processing, and interpretation. By leveraging widely used tools, such as Microsoft Project and Google Drive, the system simplifies complex workflows. The integration of a Telegram bot for streamlined image data uploading and a low-code workflow automation platform like n8n ensures accessibility for non-specialist stakeholders. This supports broader adoption in the construction industry, aligning with recent findings emphasizing the role of digital technologies in minimizing manual operations and enhancing workflow efficiency.

The automated generation of reports succeeded in capturing nuanced aspects of project progress. For instance, the system provided detailed insights into the planned versus actual status of tasks, identifying discrepancies such as the non-initiation of key activities (e.g., wall fixture installations and HVAC diffusers).

Such insights are critical for stakeholders, enabling proactive decision-making and improving a deeper understanding of site progress without requiring technical expertise. This aligns with previous studies advocating for automated reporting systems to enhance decision-making efficiency.

The case study highlights the ability of the proposed automation system to reduce bias, a major challenge in manual reporting processes. By relying on data inputs directly from site inspections and schedule updates, the developed workflow fully eliminates potential subjective interpretations often introduced by human intermediaries. For example, the categorization of tasks as "not started" or "in progress" is derived from structured data rather than personal judgment, ensuring consistency in reporting. This objectivity is further enhanced by visual evidence from 360-degree images, which provide a verifiable basis for evaluating site conditions. Such an approach aligns with findings that emphasize the role of the proposed automation workflow in enhancing transparency and objectivity in construction management.

7 Limitations and Future Work

Despite these strengths, the study identifies some limitations. First, the reliance on scheduled updates and inspection photos as primary data inputs introduces vulnerabilities to inaccuracies. For instance, the discrepancy between planned and actual progress, particularly the underreporting of completed tasks (i.e., in the case study, task “Concrete work for seating area”), underscores the need for site verification. While automation streamlines data integration, human oversight remains essential to validate outputs.

Second, the scope of the study focuses on construction progress reporting without considering cost metrics. While the SPI computation in the study provides a functional basis for assessing schedule adherence, the lack of cost-related indices limits its applicability in budget-critical projects. Future work should integrate cost parameters to provide a more comprehensive project performance evaluation. Additionally, the use of static image data and dependency on a basic interpretation of the image content introduces challenges in capturing dynamic site conditions, such as real-time adjustments to workflows or unforeseen disruptions. Moreover, without performing evaluations of the work volume, and purely relying on the evaluations performed by the MLLM, understanding the accurate extent of work from the existing information could be challenging. To address these limitations, future work should incorporate advancements in real-time data acquisition methods (e.g., automated LiDAR data acquisition), considering more information as data input (e.g., an audio voice note from the worker collecting the images clarifying details about the extent of completed work) as well as automated work volume measurement mechanisms in the workflow.

8 Conclusions

This study introduces an innovative and practical approach to automating construction progress reporting, demonstrating benefits in minimizing manual effort, reducing reporting bias, and improving workflow efficiency. A case study conducted at a university campus highlights the system’s ability to generate detailed, accurate, and accessible reports that cater to both technical and non-technical stakeholders. By integrating schedule data with image-based site inspections and leveraging MLLMs for data processing and analysis, the proposed approach effectively bridges the gap between traditional reporting methods and the evolving demands of modern construction management. This integration ensures seamless data processing, enhances reporting accuracy, and supports more informed decision-making throughout the project lifecycle.

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