AN AUTONOMOUS DRONE FRAMEWORK FOR REAL-TIME 3D CONSTRUCTION MONITORING USING PHOTOGRAMMETRY AND IOT TECHNOLOGIES

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Abstract

This paper presents an innovative framework for autonomous 3D construction site monitoring using drones, photogrammetry, and Internet of Things (IoT) technologies. The proposed system captures 2D images of construction sites via a custom-built drone, which transmits the images in real-time to cloud services for immediate processing. Using Amazon Web Services (AWS), the images are automatically reconstructed into detailed 3D models, enabling remote monitoring and progress tracking. The system leverages Industry 4.0 technologies to facilitate cloud-based data analysis, offering a scalable and efficient solution for construction project management. We validated the framework through real-world testing at a construction site in Subang Jaya, Malaysia, where two flight missions were conducted, capturing 79 and 158 images, respectively. The 3D reconstruction was successfully performed with improved processing time on higher-specification AWS machines. Results showed that the system was able to reconstruct accurate 3D models, with Flight #2 achieving smoother surfaces compared to Flight #1, despite variations in image quality. The integration of Building Information Modeling (BIM) with the 3D models is proposed to automate the comparison of construction progress with design specifications. This approach has the potential to enhance the precision, accessibility, and efficiency of construction monitoring, particularly in environments with limited access.

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1.0 INTRODUCTION

The construction industry has increasingly relied on advanced technologies to improve efficiency, safety, and quality control. Among these innovations, drones have emerged as a valuable tool, particularly in construction monitoring, due to their ability to collect real-time, high-resolution data from difficult-to-access sites. Traditional methods of construction monitoring often require physical presence, extensive manpower, and manual data collection, which are not only time-consuming but also prone to human error. The challenge becomes even more pronounced in situations such as the COVID-19 pandemic, where access to construction sites may be restricted, and the safety of data collectors becomes a concern.

This paper proposes an autonomous 3D mapping drone framework for construction monitoring that leverages Internet of Things (IoT) technologies and photogrammetry to address these challenges. Our system enables real-time data collection and analysis without the need for on-site personnel, including on-the-fly processing of cloud computational tasks and final 3d model visualisation. The drone autonomously captures images of the construction site, which are then uploaded to the cloud for 3D reconstruction using photogrammetry. This reconstruction process provides a highly detailed and accurate 3D model of the site, enabling remote monitoring and assessment by construction experts.

The use of photogrammetry, which converts 2D images into a 3D model, offers a cost-effective solution by reducing the need for expensive equipment. Although photogrammetry traditionally requires significant computational power, the advent of cloud computing has made high-performance computing resources more accessible and affordable. With the integration of cloud-based services such as Amazon Web Services (AWS), the processing of large volumes of images is facilitated, and the system becomes scalable, enabling real-time monitoring for various construction projects.

The primary aim of this paper is to highlight the potential of integrating IoT and drone technologies for construction monitoring. By automating data collection and leveraging real-time cloud-based analysis, this system has the potential to revolutionise how construction projects are monitored, leading to better oversight, improved decision-making, and enhanced safety protocols. This work also aims to share insights into the development of both the hardware and software frameworks used in the system, providing a valuable reference for the research community interested in this area.

2.0 RELATED WORKS

The use of unmanned aerial systems (UAS), commonly known as drones, in the construction industry has gained significant attention over the past decade. Drones offer numerous advantages in construction monitoring, particularly in tasks such as site surveying, progress monitoring, and damage assessment. A systematic review by Zhou and Gheisari (2018) categorised UAS applications into various areas, including building inspection, site surveying, and progress monitoring. However, progress monitoring only contributed to 5.6% of UAS applications in the construction sector, highlighting the need for further research and development in this area.

In the context of construction monitoring, drones have been increasingly used to assess the ongoing status of construction projects. According to Lin *et al.* (2015), drones allow construction teams to capture high-quality images that can be superimposed onto Building Information Models (BIM) to monitor progress. This approach provides a lower-cost, more efficient method for site inspection compared to traditional methods. Additionally, drones offer a broader field-of-view, improved accessibility, and reduced monitoring time. The integration of photogrammetry with drones has also been explored as a means of enhancing the accuracy and detail of construction monitoring. For example, Lee *et al.* (2019) proposed a voxel-based comparison method where images captured by drones were processed into a 3D point cloud model using photogrammetry. This 3D model was then compared to the BIM model, providing periodic progress assessments. Similarly, Arif and Khan (2021) introduced a smart progress monitoring framework using video recordings, MATLAB, and BIM, while Casierra *et al.* (2022) used Agisoft Metashape for manual photogrammetric reconstruction. Although effective, these methods often involve manual workflows that could be improved with automation.

The challenge of automating drone-based construction monitoring was addressed by Patel *et al.* (2021), who utilised Pix4D software for progress monitoring. However, the use of proprietary software limited the system's flexibility and scalability. In contrast, our approach leverages open-source photogrammetry and cloud computing to automate the 3D reconstruction process, providing a more scalable and cost-effective solution.

Several reviews have highlighted the benefits and limitations of drone-based inspections for construction applications. Falorca *et al.* (2021) focused on the use of high-resolution cameras for visual inspections, while Konikov and Garyaev (2021) reviewed information technology (IT) solutions for progress monitoring in construction. However, these studies did not delve deeply into the integration of IoT and cloud-based systems for real-time monitoring, an area that our research aims to address.

Recent advancements have focused on automating construction monitoring through UAVs. For instance, Girgin *et al.* (2025) developed an EdgeAI-enabled drone system for autonomous construction site surveillance. Their system integrates lightweight object detection models within a custom-built UAV platform, facilitating real-time obstacle detection and dynamic path planning in construction environments. Field experiments demonstrated the system's scalability and computational efficiency compared to existing UAV solutions.

The combination of photogrammetry and IoT technologies has been extensively studied for construction monitoring. For example, Choi *et al.* (2024) integrated drone imagery with Building Information Modeling (BIM) to enhance construction site management. Their approach utilised photogrammetry for accurate 3D modeling, while IoT sensors provided real-time environmental data, facilitating informed decision-making.

Table 1: Comparative existing systems and proposal

Study	UAV Type	IoT Integration	Data Processing	Automation Level	Scalability	Key Limitation
Girgin *et al.* (2025)	Custom-built	EdgeAI-enabled	Real-time obstacle detection	High	High	Limited to specific construction tasks
Choi *et al.* (2024)	Commercial drones	IoT sensors	Cloud-based BIM integration	Moderate	Moderate	Requires manual UAV operation
Xu *et al.* (2021)	Standard UAVs	None	Offline data processing	Low	Low	Not real-time; lacks IoT integration
Sah *et al.* (2024)	N/A	N/A	N/A	N/A	N/A	Focuses on barriers, not solutions
Ko *et al.* (2025)	UAV with LiDAR	None	LiDAR-based 3D point cloud processing	High	High	High hardware cost and limited in GPS-denied environments
Liu *et al.* (2025)	UAV with LiDAR and Vision	None	LiDAR and vision-based data fusion	High	High	Complex data interpretation
Zhang *et al.* (2024)	UAV with LiDAR	None	LiDAR-based 3D modeling	High	High	High hardware cost; limited in dense environments
Proposed Framework	Autonomous Drone (Custom-built)	IoT-enabled for Real-time Monitoring	Real-time 3D image reconstruction on the cloud	High	High	Full automation requires cloud computing and advanced photogrammetry software

Despite technological advancements, several challenges hinder the widespread adoption of UAVs in construction. Sah *et al.* (2021) identified key barriers to drone implementation in sustainable construction, including regulatory issues, technical limitations, and economic constraints. Their study emphasises the need for clear regulatory frameworks and industry-wide training programs to facilitate broader adoption.

Efficient data processing is crucial for real-time construction monitoring. Xu *et al.* (2024) proposed a volumetric change detection framework using UAV oblique photogrammetry to monitor building collapse. Their method involved multi-temporal UAV images and 3D point clouds, enabling precise detection of structural changes over time. Despite the clear potential of drones in construction monitoring, the widespread adoption of this technology has been hindered by factors such as technical complexity, high costs, and lack of awareness among construction professionals (2021).

Numerous studies have demonstrated the effectiveness of drone-based data acquisition for creating highly detailed 3D models using various sensors, including LiDAR and RGB cameras (Ko *et al.,* 2025). These models are instrumental for conducting structural health assessments, offering an alternative to traditional methods that are time-consuming and labor-intensive. For instance, LiDAR technology has proven advantageous in accurately capturing the geometry of buildings and infrastructure (Zhang *et al.,* 2024), while computer vision techniques have been applied to analyse drone-captured imagery for defect detection and real-time progress tracking (Lee & Kim, 2024). Moreover, advancements in data fusion techniques, such as combining LiDAR and RGB data, have been explored to further enhance the accuracy of 3D models (Liu *et al.,* 2025). However, despite these advancements, several critical challenges remain, including the integration of real-time data processing, the high cost of hardware, and the complexity of interpreting large volumes of data.

In this work, the integration of autonomous drones with IoT technologies and cloud-based photogrammetry for real-time 3D construction monitoring will result in an efficient, scalable, and accurate system capable of providing detailed and timely insights into construction progress. This system will outperform traditional methods by automating the image capture and processing workflow, enabling continuous monitoring of construction sites with minimal human intervention. To overcome the challenges identified, we compare this approach with existing systems in Table 1 and propose an autonomous drone framework that integrates IoT technologies to facilitate real-time 3D mapping and construction monitoring, with performance metrics (such as RMSE values and processing times) meeting industry standards for real-time data analysis.

3.0 FRAMEWORK

This section describes the proposed IoT-based framework for automated construction monitoring using drone technologies. The framework consists of four key components: (1) the computer system used for flight planning and data management, (2) the embedded drone system for image acquisition, (3) the data server for storing images, and (4) the web server for real-time data analysis and monitoring.

3.1 Overview of the Framework

The framework is designed to provide an autonomous system that captures and processes construction site images using drone-based technology. The drone is responsible for flying over the construction site and capturing images of the site's progress. These images are then transmitted in real-time to a cloud server, where photogrammetry techniques are applied to generate 3D models of the site. The data is then analysed by construction experts via a web server, facilitating remote site monitoring. Key components of the framework:

i. Computer System:
   - The computer is responsible for setting up and optimising the drone system, including flight planning. The computer also connects to the web server to access and analyse 3D image reconstructions on the cloud.
   - Flight Planning: The computer plays a central role in creating the flight path for the drone. The flight path is optimised for comprehensive image acquisition over the construction site.

ii. Embedded Drone:
   - The embedded drone system captures images of the construction site using a camera mounted on the drone. GPS data is used to track the location of the drone and ensure that the images are acquired from the correct positions.
   - The drone is connected to the cloud via mobile data, enabling real-time transmission of images to the server.

iii. Data Server:
   - The AWS (Amazon Web Services) data server is used to store images transmitted from the drone. The data is processed for 3D image reconstruction using photogrammetry. The server allows experts to access images and reconstructed models for further analysis.

iv. Web Server:
   - The web server facilitates real-time monitoring of the construction site by the experts. They can remotely analyse the 3D models and images via a user interface.

3.2 Components of the System

3.2.1 Computer System

The computer system plays a pivotal role in setting up and controlling the drone for image acquisition. It is used to configure the flight path and ensure the drone's autonomy during the image capture process. In this work, the flight path is optimised for high-quality image acquisition using the drone's GPS system.

The computer system also connects to the web server, allowing the 3D image data to be uploaded to the cloud for reconstruction and analysis. This process can be done in real-time or on-demand, depending on the needs of the project.

3.2.2 Embedded Drone System

The embedded drone system is equipped with a camera, GPS, and a communication module for real-time data transfer. The drone is constructed with a Raspberry Pi as the central controller, allowing the addition of peripherals such as cameras and communication modules. The drone is designed to be lightweight, making it suitable for carrying and operating in various construction environments.

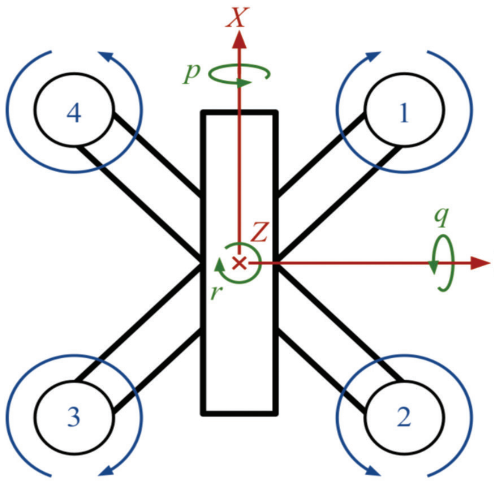

Figure 1: Quadcopter-based drone

The drone operates autonomously, capturing images of the construction site from multiple angles. To ensure precise image acquisition, GPS data is used to track the drone's location. Additionally, the drone is connected to the AWS cloud via mobile data (GSM module), enabling real-time transmission of the captured images.

- Camera: A budget-friendly action camera (SJ4000 series) is used for image capture. The camera is equipped with a 12-megapixel CMOS sensor and is designed for outdoor use, making it robust enough for construction environments.
- GPS: The GPS system tracks the drone's location in real time, ensuring that the images are captured from the correct location.

The drone was custom-built using a Raspberry Pi as the central controller. A body-fixed coordinate system based on the quadcopter's configuration is adopted for this study, as depicted in Figure 1. The drone features a 450mm wheelbase and is equipped with a 30A electronic speed controller (ESC) and a 10-channel receiver. It is powered by four 1000kV brushless DC motors, two of which rotate clockwise, while the other two rotate counter clockwise. A key advantage of using brushless DC motors is their ability to generate minimal electromagnetic interference, which helps reduce potential disturbances to the drone's sensors. The 30A pulse-width modulation (PWM) ESC module is used to control the motors. Proper calibration of the ESC and motors is essential for their synchronisation. The drone is powered by a 3S1P 25C 11.1V 3300mAh LiPo battery.

The drone's path planning algorithm computes a set of waypoints that define the flight route based on the mission parameters. These waypoints are dynamically adjusted based on real-time sensor data and environmental changes. ArduPilot's mission planner is utilised to program the waypoints, and the onboard system updates the drone's flight path to follow a predefined trajectory. This allows for both autonomous and semi-autonomous operation modes, where the drone can adjust its path or speed in response to real-time conditions.

The ArduPilot Mega 2.8 is utilised as the flight controller module, offering an autopilot function that ensures smooth and stable flight, including autonomous take-off and landing. This module, which operates on open-source firmware, supports custom drone development and settings. A 915MHz telemetry radio is employed for communication with the drone, with a 100mW (20dBm) output power that allows radio control up to nearly 1 km. The receiver is attached to the flight controller, while the transmitter is connected to the laptop. Unlike the transmitter, the receiver may require modification using an adapter (e.g., CP2012 FTDI) for firmware updates.

When flying in unpredictable conditions such as turbulent weather, the system uses real-time flight data to adjust the drone's control surfaces, motor speeds, and flight parameters dynamically. ArduPilot's real-time flight stabilisation algorithms adjust these parameters to mitigate the effects of turbulence or wind gusts, ensuring steady flight. The system continuously monitors the drone's performance, including battery consumption, motor health, and sensor accuracy. ArduPilot's internal health monitoring system alerts operators to any performance issues, allowing for preemptive maintenance or adjustments during flight. Autonomous flight algorithms also consider energy efficiency, adjusting the drone's flight speed and altitude to minimise power consumption while maintaining optimal path tracking and task execution.

For navigation, the NEO-M8 series module is paired with the flight controller, supporting up to three global navigation satellite systems (GNSS): GPS, Galileo, BeiDou, and GLONASS. Additionally, this module includes jamming and spoofing detection capabilities to enhance security, reducing the risk of flight loss or entering restricted areas. A 10-channel radio-based transmitter and receiver, the Flysky FS-i6b, is used for flight control. While the drone requires only four channels to control its motors, an additional four channels are necessary for initiating a failsafe mechanism during emergencies or to avoid crashes.

For cloud connectivity, a SIM7600E-H 4G HAT is used as the GSM module for real-time communication. There are no specific requirements for this module, other than ease of integration with the Raspberry Pi and low power consumption. Construction site images were captured using a budget-friendly action camera, the SJ4000 series, which features a 12-megapixel CMOS sensor. Weighing just 58g, the camera is compact and lightweight. Its robust design makes it well-suited for outdoor environments, making it an ideal choice for drone applications. The overall framework is shown in Figure 2, and the hardware architecture is presented in Figure 3.

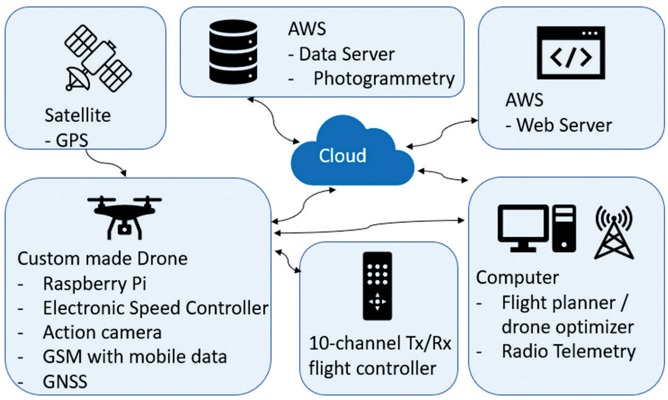

Figure 2: Overview of the Autonomous 3D Mapping Drone Framework

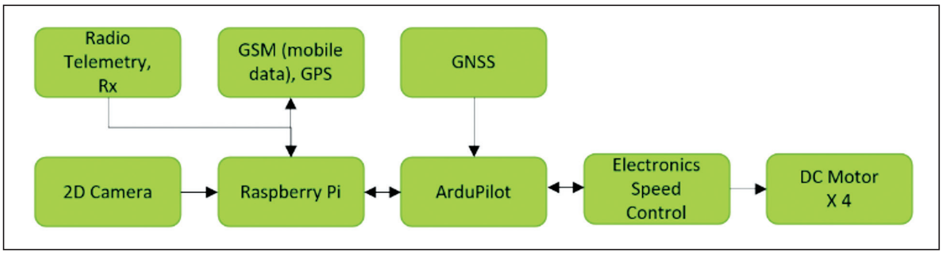

Figure 3: Hardware Architecture of the System

3.2.3 Data Server and Cloud Integration

The overview of the proposed autonomous 3D mapping drone for construction monitoring is shown in Figure 4.

Planning the flight is crucial for ensuring the safety and success of the mission. In this study, construction site images are captured from multiple locations and angles to provide a comprehensive view. The oblique mapping method is employed for construction monitoring, where the camera is positioned at a 60-degree angle relative to the drone's plane.

For autonomous flight control, we used the "ArduPilot Project" with its configuration utility to enable advanced dynamic control. The "Arducopter 3.2.1" firmware is first uploaded to the autopilot board (APM), allowing customisation of the drone's behavior, including motor control programming through Microsoft Visual Studio. Once the firmware is installed, the drone is set up, configured, and optimised for performance. The flight plan is then created by simply selecting points on Google Maps for waypoints. APM generates the flight plan, which can be downloaded for further analysis. Additionally, the system allows interfacing with a flight simulator on a personal computer to recreate unmanned aerial vehicle (UAV) telemetry, providing the ability to monitor, record, and analyse telemetry logs.

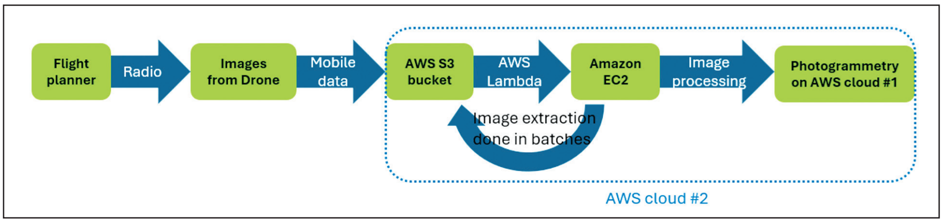

Figure 4: The software architecture of an autonomous 3D mapping drone

In this study, Internet-of-Things (IoT) devices are connected to cloud services for automated digitisation. We utilised Amazon Web Services (AWS) as the core Internet 4.0 technology for autonomous 3D drone mapping in construction monitoring. The AWS cloud system is divided into two categories: (1) AWS Cloud #1 and (2) AWS Cloud #2, as shown in Figure 4. AWS Cloud #1 consists of AWS Simple Storage Service (S3), AWS Lambda, and AWS Elastic Compute Cloud (EC2). Images are initially stored in an AWS S3 container by the user. Once received, AWS Lambda, a serverless computing service, is triggered and requires user input to initiate. After being triggered, the images are transferred from AWS S3 to AWS EC2 for storage. AWS EC2 continuously extracts images from AWS S3, and careful supervision is necessary once the service is running. The images in AWS S3 remain in the container as a backup in case any images stored in AWS EC2 become corrupted. AWS Cloud #2 handles IoT automation. Images acquired from the drone's camera are sent to the AWS Command Line Interface (CLI) via mobile data. Once interfaced with AWS Cloud #1, the data is automatically synced to AWS EC2. It is important to note that the architecture of AWS Cloud #1 should be modularised to support multiple AWS CLI connections from various IoT-based edge devices.

For cloud security, AWS Identity and Access Management (IAM) is employed. AWS IAM allows for precise control over user access, specifying the permissions for various operations. Each user has restricted access when logging into the AWS Management Console and interacting with resources. Additionally, new users can register with their credentials, and the principal must authenticate their "exceptional" rule for access.

3.2.4 3D Image Reconstruction, Web Server, and Monitoring

The 2D building images captured on-site are reconstructed into a 3D model using photogrammetry techniques for construction monitoring. As the 2D images are already stored in the cloud (AWS EC2), Meshroom 3D Reconstruction software, utilising the AliceVision framework, was employed to develop the 3D model of the construction site. The command-line interface (CLI) of Meshroom is integrated with AWS CLI to enable autonomous 3D image reconstruction on the cloud. Meshroom is an open-source software, allowing users to troubleshoot any issues that may arise during the reconstruction process.

The performance of the 3D reconstruction heavily depends on both the quality of the 2D images captured by the drone and the available computing power. To ensure high-quality results, images were captured from a 360-degree view around the building, covering as many points as possible. Once the collection of images is received from the cloud, the software processes them through several stages: feature extraction, image matching, feature matching, structure-from-motion, depth map estimation, meshing, and texturing, ultimately reconstructing the 3D model. An example of 2D to 3D image reconstruction is shown in Figure 5.

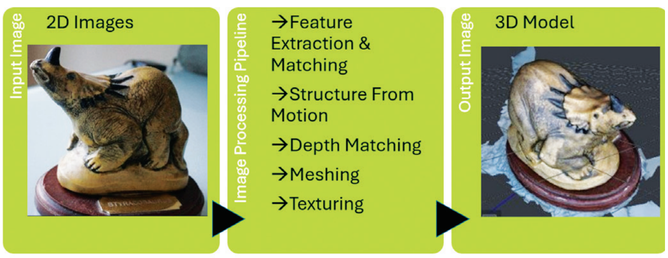

Figure 5: Photogrammetry image processing pipeline

To input images, multiple files are dropped into the designated drop box. The process begins with camera calibration, which retrieves internal camera parameters such as focal length, sensor width, principal points, and distortion parameters. Meshroom utilises OpenCV, a real-time computer vision library, to perform the camera calibration. The source code for camera calibration is available in the OpenCV library and can be accessed through its official website.

For feature extraction, the SIFT (Scale-Invariant Feature Transform) algorithm is used to extract distinct groups of pixels. The algorithm first identifies keypoints from a multiscale image representation, followed by the extraction of descriptors associated with each keypoint. These descriptors, stored as 128-bit vectors, represent gradients around the keypoints and enable the matching of keypoints across different images. The scale-space maxima are computed using the difference-of-Gaussian function, which convolves the image with a variable-scale Gaussian, as defined by the Laplacian representation. Once the features are extracted, image retrieval techniques, such as the vocabulary tree approach, are used to match similar areas from different images, allowing the software to recognise shared content through image descriptors.

The core of 3D reconstruction from multiple images occurs in the Structure-from-Motion (SfM) process, a photogrammetric technique used to construct rigid scene structures or 3D points from 2D image sequences. During feature extraction and matching, points are fused to create tracks, with each track representing a point in space visible from multiple camera angles. SfM utilises various algorithms, such as the Next Best View Selection, which chooses images with sufficient associations to the features already reconstructed in 3D.

The resectioning process involves a Perspective-n-Point (PnP) algorithm in a RANSAC framework to determine the camera pose that best validates feature associations. To refine the pose further, non-linear minimisation is performed on each camera, and this process repeats to triangulate new points, adding and removing cameras until no new views can be localised. SfM is optimised through the use of high-scale SIFTs, which provide a coarse model that enables faster results by adding cameras and points simultaneously, rather than sequentially. This method accelerates the process by utilising more computational power. Additionally, libraries such as OpenCV and Ceres Solver are employed in the SfM process to handle tasks like pose estimation, triangulation, and point-cloud alignment, resulting in a 3D model. Depth mapping involves extracting image information related to the distance from a scene at a specific viewpoint. After the Structure-from-Motion (SfM) process, the depth value of each pixel is retrieved during this stage of the pipeline.

The method used for depth mapping in Meshroom, powered by AliceVision, employs the Semi-Global Matching (SGM) technique. The algorithm consists of four key steps: (i) pixelwise cost calculation, (ii) smoothness constraint implementation, (iii) disparity computation with sub-pixel accuracy and occlusion detection, and (iv) multi-baseline matching extension (Hirschmüller, 2005). When combined, these steps allow for precise depth mapping, enhancing the accuracy of 3D model construction by reducing errors and ensuring consistency across multiple viewpoints.

During the Meshing stage, a dense geometric surface representing the scene is created through 3D Delaunay tetrahedralisation, along with additional methods like Laplacian filtering and Poisson smoothing to improve the mesh. Meshing is critical for 3D visualisation and measurement. In the texturing step, the Least Squares Conformal Maps (LSCMs) approach is used to apply texture to the mesh, minimising texture distortion. Once texturing is complete, the 3D reconstruction process is finished, and the model is saved in a user-specified directory. A 'Texturing' folder within this directory contains the final 3D model, ready for viewing.

The web server provides a platform for construction experts to monitor the progress of the construction site remotely. After 3D reconstruction, the 3D model is made available on the server for analysis. The server connects to the data server and provides a graphical user interface for the experts to review the site's progress.

3.3 Data Flow and Real-Time Processing

The data flow within the system is designed to facilitate the seamless acquisition, processing, and analysis of construction site data. The drone captures images of the site, which are sent to the cloud server in real-time via mobile data. Once the images are uploaded to the cloud, they are processed using photogrammetry techniques to generate a 3D model of the construction site.

This model is then made available for remote analysis on the web server. By using cloud computing resources, the system can handle large volumes of image data and process them quickly, providing real-time feedback to construction experts.

4.0 EXPERIMENT AND RESULTS

This section details the experiments conducted to validate the proposed autonomous 3D mapping drone framework for construction monitoring. The framework was tested in a real-world construction site in Subang Jaya, Selangor, Malaysia, to assess its capability in capturing, processing, and analysing construction site data. The experiments included two flight missions with varying numbers of images, and the results of these missions were used to evaluate the effectiveness of the system.

4.1 Experimental Setup

Two flight missions were conducted to test the system:

- Flight #1: The drone captured 79 images.
- Flight #2: The drone captured 158 images.

The images were sent to the AWS cloud in real-time for processing and 3D reconstruction. The drone used GPS data for accurate flight navigation, and the captured images were processed using the Meshroom 3D Reconstruction software on the cloud.

4.2 Data Collection and 3D Reconstruction

The drone followed a pre-planned flight path, and images were captured from multiple perspectives to ensure complete coverage of the construction site. These images were then uploaded to the cloud and processed using photogrammetry software (Meshroom), which converts the 2D images into a 3D model. Once the models were reconstructed, they were made available for review on the web server for construction experts to analyse the site's progress remotely.

4.3 Experimental Findings

The experimental results are summarised in the following Table 2, which compares the processing time, image quality, and 3D model accuracy for the two flight missions.

Table 2: Experimental results

Experiment	Flight #1 (79 images)	Flight #2 (158 images)
Processing Time (g4dn.xlarge)	1 hour, 55 minutes	3 hours, 50 minutes
Processing Time (g4dn.4xlarge)	50 minutes	1 hour, 55 minutes
3D Model Quality	Fewer surface bumps, but less smooth than Flight #2	Smoother surface with fewer visible defects
Comparison with Cathedral Model (Meshroom)	Rougher texture, less detailed	Smoother texture, better detail
Image Acquisition	Good coverage, but lower number of images may affect accuracy	Higher number of images results in a more detailed model
Flight Path Deviation	Minor deviation from the planned path	Minor deviation, but sufficient data was still captured

The cloud-based machines used were equipped with high-performance specifications to ensure fast data processing for 3D image reconstruction. The two machines used were as follows:

- g4dn.xlarge: This machine is equipped with 4 virtual CPUs and 16 GB of RAM. It is suitable for tasks requiring moderate computational power, like handling image processing in real-time, but it has limitations when dealing with larger datasets.
- g4dn.4xlarge: A higher-spec machine with 16 virtual CPUs and 64 GB of RAM, designed for more demanding computational tasks, such as faster 3D image rendering and data analysis.

Both machines were equipped with a 2nd generation Intel Xeon CPU and an NVIDIA T4 Tensor Core, providing the necessary computational power for efficient processing. The experiments were performed on these two machines to compare their performance, particularly in terms of rendering time and processing speed.

The processing time was significantly shorter for Flight #1 when using the g4dn.4xlarge machine, completing the reconstruction in just 50 minutes, compared to 1 hour and 55 minutes for Flight #2 with 158 images. As expected, the larger number of images required more computational resources, resulting in longer processing times, especially on lower-performance machines like g4dn.xlarge.

The 3D model generated from Flight #2 (158 images) exhibited a smoother surface and fewer visible defects compared to the model from Flight #1 (79 images). The larger number of images contributed to a higher-quality reconstruction with more detail, making it more suitable for construction monitoring. When compared to the reference Cathedral model, Flight #2's 3D model was closer in quality, with fewer visible imperfections.

Both flights showed minor deviations from the planned flight path, likely due to environmental factors such as wind. However, these deviations did not significantly impact the quality of the acquired images, and the drone was still able to cover the construction site effectively. An illustration of this flight plan is shown in Figure 6.

Flight #2, with 158 images, provided a more detailed 3D model, demonstrating the importance of capturing a larger number of images for accurate reconstruction. This was especially important for capturing hard-to-reach areas of the site, ensuring complete coverage. An illustration of construction monitoring from 2D to 3D image reconstruction is shown in Figure 7. The experimental results demonstrate that the proposed autonomous drone framework is effective in capturing high-quality images and processing them into detailed 3D models. Key findings include:

- Real-time Processing: The system's ability to transmit images in real-time to the cloud and process them quickly is a major advantage for construction monitoring. The use of AWS cloud computing enables efficient processing, even for large datasets, reducing the time required for analysis.
- Data Quality: The quality of the 3D models improved significantly with a higher number of images. While the model from Flight #1 provided adequate detail, Flight #2 produced a more accurate and refined 3D representation of the construction site, suggesting that future work should focus on optimising image capture for even higher accuracy.
- Efficiency and Scalability: The system performed well for both small-scale (79 images) and larger-scale (158 images) construction monitoring, showing that the framework can scale to handle different sizes of projects.

To evaluate the accuracy of the 3D reconstruction and to quantify the quality of the generated 3D models, we used Source Filmmaker (SFM), a computer graphics tool, to compute the Root Mean Square Error (RMSE) of the 3D scenes. The RMSE is a measure of the difference between the reconstructed 3D model and the reference model. A lower RMSE indicates a more accurate reconstruction.

The 3D reconstruction process yielded better results when more images were used, compared to the computational power of the machine for rendering. The table below presents the SFM RMSE values for the two flight missions using different machine configurations: g4dn.xlarge and g4dn.4xlarge.

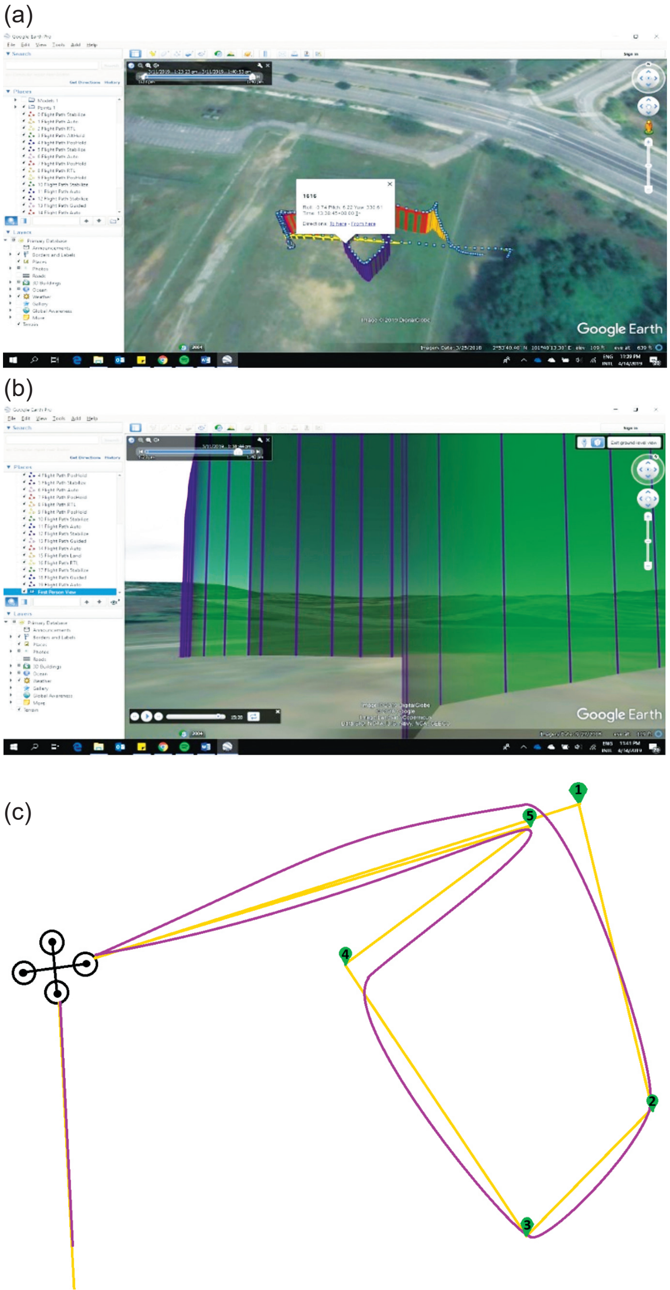

Figure 6: Flight planning and results
(a) Google Earth flight path overview, (b) first-person view (fpv) from drone, and (c) completed flight mission with path representations in yellow (planned) and purple (actual)

For Flight #1 (79 images), the RMSE was higher (1.44266 for g4dn.xlarge and 1.44154 for g4dn.4xlarge) compared to Flight #2 (158 images). This indicates that the model generated with fewer images had more discrepancies compared to the model generated with a larger dataset. The RMSE values for Flight #2 were lower (1.38934 for g4dn.xlarge and 1.38073 for g4dn.4xlarge), suggesting that the model was more accurate with more images used for reconstruction. Referring to Table 3, the RMSE does not show significant improvement with increased computing power. Flight #1 and Flight #2 showed a minimal improvement of 0.078% and 0.062%, respectively. However, a more noticeable reduction in RMSE, ranging from 3.7% to 4.2%, is observed as the number of images increases, depending on the computing power.

When compared with the Meshroom Cathedral 3D model, which has a smoother and more detailed surface due to its use of 350 images, our Flight #2 model performed better with an RMSE of 1.38073 for g4dn.4xlarge. Although the RMSE is still higher than the ideal value of 0.6, it is considered a good result for a smaller number of images and demonstrates the potential of this framework for real-time construction monitoring. The Meshroom Cathedral model had a RMSE of around 0.6, which serves as a benchmark for high-quality 3D reconstructions. Given the lower number of images in our experiment, achieving an RMSE close to 0.6 would require improving the image acquisition process, such as using a higher-quality camera and capturing more images.

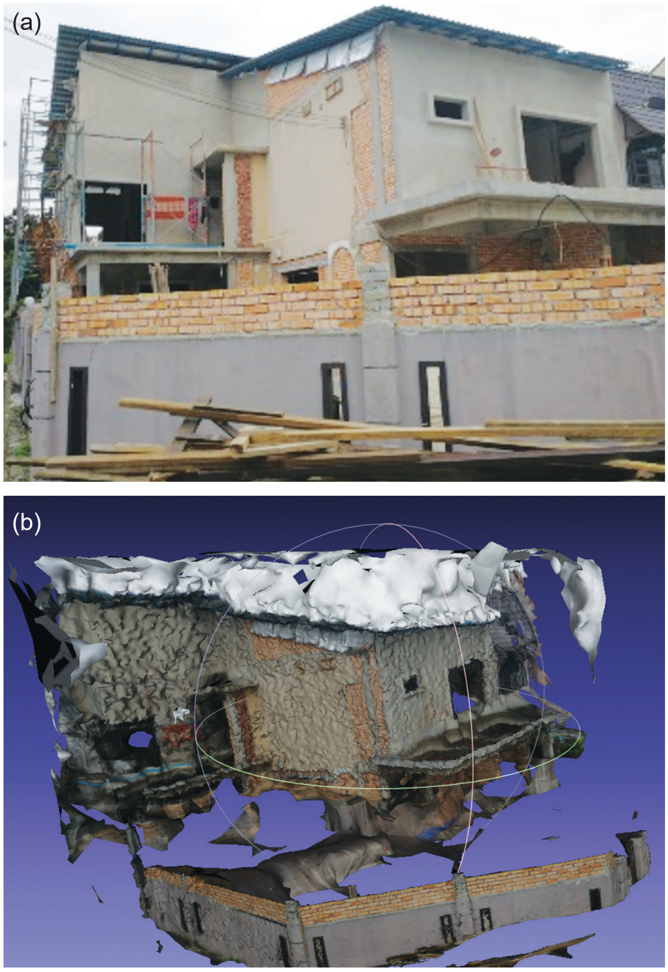

Figure 7: Construction monitoring
(a) An example of a 2D building image, and (b) an autonomous 3D reconstructed image for construction monitoring

Table 3: Source Filmmaker results

Flight Mission	g4dn.xlarge (RMSE)	g4dn.4xlarge (RMSE)
Flight #1 (79 Images)	1.44266	1.44154
Flight #2 (158 Images)	1.38934	1.38073

The system successfully captured images from the construction site and uploaded them to the AWS cloud in real-time using GSM mobile data. This real-time data transmission allows for near-instantaneous processing of images and 3D reconstruction, facilitating remote construction monitoring. In cases where mobile data is interrupted, the images are temporarily stored on the drone and uploaded to the cloud when the network connection is restored. This ensures continuous image capture without losing data, making the system more robust in environments where mobile data coverage may be unstable. The real-time data transfer and processing via the AWS cloud enable experts to monitor construction progress remotely and in near real-time. This approach minimises the need for on-site personnel and allows for faster decision-making, especially in dynamic construction environments.

To achieve a lower RMSE and improve the accuracy of 3D models, it is essential to use higher-resolution cameras with better image quality. This would reduce visible imperfections and enhance the quality of the generated 3D models. Increasing the number of images captured during the drone flights will likely improve the model's accuracy, reducing the RMSE. Using a more comprehensive set of images from various angles can enhance model detail and reduce occlusion, especially in complex construction environments.

Despite the advancements in autonomous flight and real-time navigation offered by the proposed method, several limitations need to be addressed for its full operational potential. First, the reliance on GPS-based systems for localisation can become a significant challenge in GPS-denied environments such as indoor or urban settings with high signal interference, where the proposed method resorts to visual-inertial odometry (VIO) or sensor fusion techniques. While these approaches offer resilience, they still struggle with accuracy and drift over extended periods or in feature-sparse environments, limiting the reliability of localisation.

Furthermore, the integration of ArduPilot, while robust for general flight control, may encounter performance issues in highly dynamic and unpredictable conditions, such as strong wind gusts or complex obstacle fields, where real-time path re-planning algorithms could fail to effectively account for rapid environmental changes. Additionally, the communication delay between the drone’s onboard system and the ground control station, even when using MAVLink protocol, could impact mission-critical decision-making and data exchange during time-sensitive operations.

Finally, the computational load imposed by real-time sensor data processing, particularly in high-resolution visual cameras, may lead to potential latency or power consumption concerns, limiting the duration and efficiency of long-duration missions. These limitations highlight areas where further optimisation and integration of advanced algorithms are necessary for achieving enhanced autonomy and operational efficiency in complex, real-world scenarios.

Future work should focus on integrating the 3D models with Building Information Modeling (BIM) software for a more comprehensive construction monitoring solution. This will enable the comparison of as-built models with the original BIM design to identify discrepancies and track project progress more effectively. As the number of images and the size of construction sites increase, optimising the system for faster rendering and processing, potentially through more advanced cloud computing technologies, will be important for large-scale projects.

5.0 CONCLUSION

This paper presents an autonomous 3D mapping drone framework for construction monitoring that leverages photogrammetry and IoT technologies to facilitate real-time, remote monitoring of construction sites. The proposed framework allows for efficient data collection, processing, and analysis, addressing common challenges faced in traditional construction monitoring methods, such as limited access to sites and the need for on-site personnel.

Through the experimental validation carried out on an actual construction site in Subang Jaya, Malaysia, we demonstrated that the framework is capable of autonomously capturing high-quality images, processing them into 3D models, and transferring the data to the cloud for real-time analysis. The results of the experiments showed that the system performs well, even with varying numbers of images, and that the 3D models generated from these images are accurate enough for construction monitoring and progress tracking. Notably, the system’s ability to operate autonomously, coupled with real-time data transmission to the cloud, offers significant advantages in terms of time efficiency and safety.

The comparison of different machine configurations (g4dn.xlarge vs. g4dn.4xlarge) highlighted that processing larger datasets requires more computational power, but the system is capable of scaling efficiently to handle larger construction sites. Additionally, the system's ability to manage interruptions in mobile data and continue storing images for later upload ensures robustness in environments with unstable network coverage. Although the quality of the 3D models could be improved by increasing the number of images and upgrading the camera, the current system already provides a reliable solution for real-time construction monitoring. The SFM RMSE analysis showed that with additional images and enhancements in image quality, the system can achieve even more accurate results.

For future work, the integration of the reconstructed 3D models with Building Information Modeling (BIM) software is proposed to enable the comparison of construction progress against the original design, facilitating automated analysis of discrepancies. Furthermore, optimisation of the system for larger-scale projects, including potential upgrades to the drone hardware and cloud computing capabilities, will be necessary to fully realise the potential of autonomous construction monitoring systems.

In conclusion, the proposed autonomous 3D mapping drone framework represents a significant step forward in the evolution of construction monitoring. By utilising photogrammetry, IoT, and cloud computing technologies, this framework offers a scalable, cost-effective solution for real-time, remote construction site monitoring that has the potential to enhance project management, improve safety, and reduce operational costs in the construction industry. ■

AUTHORS' CONTRIBUTIONS

- **Bhuvendhraa Rudrusamy:** Conceptualisation, writing, supervision.
- **Muhammad Azim Abdul Rahman:** Formal analysis, software, investigation, validation.
- **Mohsen Bazghaleh:** Resources, Methodology, supervision.
- **Ali Rashidi:** Supervision.

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