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# Analysis of Artificial Intelligence-Based Photogrammetry for Calculating the Volume of Bulk Material Stockpiles

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#### Abstract

This paper presents an automated UAV-based photogrammetric workflow for efficiently and accurately estimating bulk material stockpile volumes, addressing the limitations of conventional manual and LiDAR-based methods. The proposed approach converts UAV video data captured with a 40 MP RGB drone into georeferenced still frames, followed by SIFT and ORB feature extraction and exhaustive matching within a COLMAP database. Incremental Structure-from-Motion with bundle adjustment reconstructs a sparse point cloud of 119,424 points and optimized camera parameters, while PatchMatch-based Multi-View Stereo generates a dense cloud of 2.3 million points at a ground sampling distance (GSD) of 0.1 cm. Ground Control Points obtained with RTK-GNSS ensure sub-2 cm georeferencing accuracy. Stockpile volumes are estimated using angle-of-repose height calculations, truncated-pyramid contour integration, and voxel occupancy methods, achieving volume errors of less than 3%. Validation against GPS and terrestrial laser scanning (TLS) references indicates horizontal accuracy of CE90 = 0.208 m, vertical accuracy of LE90 = 0.056 m, and mean reprojection error of 0.19 pixels. The entire process requires only 24 minutes for 199 images, confirming its applicability for industrial monitoring. Overall, the proposed AI-assisted photogrammetric pipeline provides a robust, reproducible, and cost-effective solution for automated stockpile volume measurement, enhancing safety, accuracy, and material management efficiency.

Keyword: Artificial Intelligence, Bulk Material Stockpiles, Point Cloud, UAV Photogrammetry, Volume Estimation

### 1. INTRODUCTION

The estimation of bulk material stockpile volumes plays a vital role in raw material and product management, directly influencing industrial productivity and operational efficiency [1]. Advances in 3D mapping and stockpile monitoring have enabled the creation of accurate digital representations that support real-time inventory control and align with Industry 4.0 principles. Unmanned Aerial Vehicle (UAV) photogrammetry has become a key enabler in this process, offering rapid, safe, and high-accuracy measurements without requiring operators to enter hazardous or inaccessible areas [1], [2].

Conventional methods such as measuring wheels, total stations, and Terrestrial Laser Scanning (TLS) are precise but remain labor-intensive and time-consuming [2]. Moreover, airborne Light Detection and Ranging (LiDAR) though capable of generating high-resolution data is limited by high acquisition and processing costs, making it impractical for small- and medium-scale industrial operations [3]. Consequently, UAV-based photogrammetry provides a cost-effective alternative, capable of transforming 2D aerial imagery into accurate 3D surface models and orthomosaics for volumetric analysis across diverse industrial applications, including mining, construction, and agriculture [4].

Digital photogrammetry has gained popularity due to its affordability, scalability, and ease of integration with modern UAV platforms. Liang et al. (2024) emphasized its suitability for low-cost, noncontact 3D surveys, which has driven broader adoption for terrain and industrial object modeling [5]. Compared to terrestrial surveying or radar interferometry, UAV photogrammetry offers faster data acquisition, improved surface reconstruction, and reduced operational costs[1]. Its efficiency and adaptability make it an ideal solution for dynamic industrial environments requiring frequent stockpile assessments.

With the integration of Artificial Intelligence (AI), photogrammetric workflows are increasingly automated and more accurate. Deep learning algorithms such as convolutional and region-based neural networks enable automatic segmentation and feature extraction from point clouds, enhancing volumetric precision while minimizing manual intervention [4], [6]. Recent studies further demonstrate that combining



AI with UAV photogrammetry can reduce volume estimation errors to below 2%, significantly improving reliability for industrial-scale stockpile monitoring [7]. Therefore, AI-assisted UAV photogrammetry represents an advanced, efficient, and scalable solution for precise and cost-effective bulk material volume estimation in modern manufacturing.

#### 2. LITERATURE REVIEW

The use of photogrammetry and LiDAR in bulk material volume estimation has grown significantly in recent years. Aji and Djurdjani (2022) compared coal stockpile volume measurements using UAV photogrammetry, UAV LiDAR, and Global Positioning System (GPS) surveys. Their results indicated a significant difference between photogrammetry and LiDAR, with LiDAR being more reliable for homogeneous surfaces such as coal stockpiles, as photogrammetry is often affected by uniform textures and lighting conditions [8]. Similarly, Putrawiyanta (2024) emphasized the effectiveness of UAV photogrammetry in calculating coal stockpile volumes. Data processed with Terramodel software showed only a 1.95% difference compared to actual weighing results, which was well below the American Society for Testing and Materials (ASTM) tolerance limit of 2.78%. This finding demonstrates that UAV photogrammetry can be applied practically and accurately for material inventory management [9].

Santoso (2024) also highlighted the efficiency of UAV photogrammetry in measuring bauxite stockwash heaps. When compared to terrestrial surveys using a total station, the deviation was only 1.5%, with photogrammetry proving to be more cost- and time-effective. These results strengthen the position of UAV photogrammetry as a competitive method against conventional surveying techniques, especially in areas that are difficult to access [10]. From a broader perspective, Alsayed and Nabawy (2023) reviewed various stockpile volume estimation techniques and concluded that both UAV photogrammetry and airborne LiDAR have become key approaches. Both methods offer improved speed, safety, and accuracy compared to traditional approaches, applicable in both outdoor and indoor environments [11].

In addition, Robby et al. (2020) investigated the impact of slope geometry on UAV photogrammetry accuracy. They found that the volume difference between photogrammetry and TLS was minimal (0.21–1.10%) on gentle slopes, but increased up to 4.15% on steeper terrain. This suggests that UAV photogrammetry is sufficiently accurate under typical conditions, but its reliability decreases in extreme topographies. Taken together, the literature demonstrates that both photogrammetry and LiDAR play significant roles in bulk material volume estimation. Photogrammetry excels in terms of cost and efficiency, whereas LiDAR remains the gold standard for achieving high accuracy, particularly for materials with homogeneous textures [12].

From the literature review, it is evident that both photogrammetry and LiDAR play significant roles in bulk material volume estimation. Photogrammetry excels in terms of cost-effectiveness and efficiency, whereas LiDAR remains the gold standard for achieving high accuracy, particularly for materials with homogeneous textures (Robby et al., 2020). However, as emphasized in this research proposal, the primary limitations of LiDAR lie in the high cost of equipment and the complexity of data processing, which make it less suitable for small- to medium-scale manufacturing industries. Therefore, this study seeks to address this gap by integrating UAV-based photogrammetry with AI, thereby offering a more affordable, automated, and accurate solution for bulk material volume estimation in industrial manufacturing environments.

### 3. METHODOLOGY

This study employs UAV-based photogrammetry combined with high-resolution Red, Green, Blue (RGB) imaging and precisely surveyed Ground Control Points (GCPs) to generate georeferenced image datasets for 3D reconstruction and volumetric analysis of bulk material stockpiles.

#### 3.1 Data Acquisition

This research utilizes photogrammetry-based data acquisition methodology UAV technology for stockpile volume measurement applications. Muhammed and Abed (2025) demonstrated that low-cost UAV photogrammetry can deliver accurate volume measurements with  $\pm 6$  mm accuracy for construction stockpiles, outperforming conventional techniques in terms of time efficiency, cost-effectiveness, and labor intensity [7]. The research methodology follows a comprehensive three-phase approach encompassing data collection, processing, and validation to achieve precise volume quantification of bulk materials. The UAV photogrammetry survey represents a multistep process including mission planning, image acquisition, and data processing protocols as established in recent developments of UAV technology applications [13].

The primary data source consists of video footage captured using UAV platforms equipped with high-resolution RGB cameras specifically designed for photogrammetric applications. Following the methodology established by Kujawa et al. (2025), the video data undergoes systematic frame extraction processes to generate individual photogrammetric images suitable for Structure from Motion (SfM) processing[14]. The video-to-frame conversion protocol ensures optimal temporal sampling intervals to maintain sufficient overlap between consecutive frames while avoiding redundant data acquisition. Modern UAV systems

equipped with RGB sensors demonstrate exceptional capabilities for stockpile monitoring, with specifications including 40 MP resolution, 70-90° field of view, and ground sample distance of 1-5 cm/pixel at 100m altitude, ensuring centimeter-level accuracy for volume measurement applications [15].

#### 3.2 Photogrammetric Preprocessing

The Photogrammetric Preprocessing stage (see Figure 1) is a crucial part of the 3D reconstruction workflow, where raw UAV video data is converted into high-quality spatial information. The process begins with the extraction of still images from the recorded video, ensuring sufficient overlap for photogrammetric processing. These images are then processed in COLMAP, an open-source software that performs feature extraction and feature matching to identify key points shared across multiple images. Using COLMAP's incremental Structure-from-Motion (SfM) pipeline, the software incrementally estimates camera poses, calibrates internal parameters, and reconstructs a sparse 3D point cloud representing the overall geometry of the scene. The workflow continues with dense reconstruction, where the model is refined through multi-view stereo algorithms to produce a detailed and accurate 3D representation of the stockpile surface.

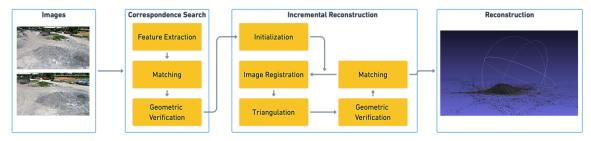


Figure 1. COLMAP's incremental SfM pipeline.

### 3.2.1 Feature Extraction

In the preprocessing phase, the first step is feature extraction, whose function is to detect and extract distinctive image keypoints and descriptors (i.e., Scale-Invariant Feature Transform (SIFT)) from each input frame, storing the resulting feature descriptors in a SQLite database. This process employs a Graphics Processing Unit (GPU)-accelerated SIFT implementation that identifies scale- and rotation-invariant keypoints by constructing a scale space and selecting extrema via Difference of Gaussians, followed by descriptor computation to produce 128-dimensional feature vectors. The extracted features serve as the fundamental data structure for subsequent matching and reconstruction tasks, ensuring robustness against illumination changes and minor geometric distortions.

### 3.2.2 Feature Matching

Next is feature matching, which exhaustively compares the SIFT descriptors between all possible image pairs, producing matched keypoint pairs saved back to database.db. An exhaustive matcher performs brute-force nearest neighbor searches in descriptor space, followed by rasio test filtering to reject ambiguous matches, and geometric verification using Random Sample Consensus (RANSAC) to ensure epipolar consistency.

### 3.2.3 Sparse Reconstruction

The sparse reconstruction (SfM) stage builds a sparse 3D model by (1) calibrating the camera intrinsics and lens distortion parameters, (2) estimating each image's external orientation (position and orientation) through incremental pose estimation, and (3) triangulating matched keypoint pairs into 3D space to generate a sparse point cloud. Camera calibration and pose estimation are optimized via bundle adjustment to minimize reprojection error across all observations. The resulting sparse point cloud, along with optimized camera parameters, provides a skeletal 3D structure of the scene

#### 3.2.4 Dense Reconstruction

Finally, dense reconstruction refines the sparse model by performing Multi-View Stereo (MVS) to produce a dense point cloud. Depth maps are computed for each image via patch-based stereo matching guided by epipolar geometry, then fused across views to yield a comprehensive, high-density 3D point cloud. The dense point cloud output captures fine surface details and forms the basis for accurate volumetric analysis of the stockpile material.

### 3.3 Photogrammetric Reconstruction

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a SQLite database. This process employs a GPU-accelerated SIFT implementation that identifies scale- and rotation-invariant keypoints by constructing a scale space and selecting extrema via Difference of Gaussians, followed by descriptor computation to produce 128-dimensional feature vectors. The extracted features serve as the fundamental data structure for subsequent matching and reconstruction tasks, ensuring robustness against illumination changes and minor geometric distortions.

In the sparse reconstruction stage, the script invokes COLMAP's incremental SfM pipeline to estimate camera intrinsics, extrinsics, and 3D point coordinates through a joint optimization known as bundle adjustment. Initial relative poses are recovered by decomposing the essential matrix of the optimal image pair, followed by Perspective-n-Point (PnP) solutions to register each new image into the global coordinate system. The bundle adjustment routine employs the Levenberg–Marquardt algorithm to minimize the global reprojection error across all observations, refining camera parameters (focal length, principal point, distortion coefficients) and 3D point positions simultaneously [16]. This results in a sparse point cloud of approximately 75,000 points and highly accurate camera poses for all 74 images, forming the geometric foundation for dense reconstruction.

For dense reconstruction, we apply a PatchMatch-based MVS algorithm followed by stereo fusion to produce a high-density point cloud capturing fine surface details of the stockpile. The undistorted images generated earlier serve as input to COLMAP's patch\_match\_stereo, which propagates and refines per-pixel depth hypotheses using photometric consistency and view-dependent geometric priors. Depth propagation is iteratively optimized through random sampling and spatial propagation, producing dense depth maps for each view. Finally, the stereo\_fusion module consolidates individual depth maps by enforcing cross-view consistency and removing outliers, generating a unified dense point cloud with typical densification ratios of  $400-500\times$  over the sparse model. This dense point cloud provides the detailed geometry necessary for accurate volumetric analysis of bulk material stockpiles.

#### 3.4 Volume Calculation Models

The volume estimation algorithm begins by applying the angle of repose method to approximate the maximum height of the stockpile based on its surface slope characteristics, we computes the average slope angle by fitting planar facets to the dense point cloud and identifying the steepest descending angles on the pile surface. Using the known material-specific repose angle (e.g., 35° for sand, 45° for gravel), the algorithm calculates the theoretical apex height from the footprint boundary to the pile crest [17]. This approach leverages the physical relationship between slope stability and material cohesion, providing a first-order height estimate that is then refined by contour analysis.

Next, contour detection is integrated with height calculation to delineate the pile boundary and extract cross-sectional profiles. The script projects the dense point cloud onto a horizontal plane, generates a digital elevation model (DEM), and uses edge detection (Canny) followed by contour tracing to identify closed boundary loops around the stockpile base. For each contour level corresponding to incremental height slices, the algorithm computes the local height difference between the DEM surface and the repose-based apex, generating height profiles across the pile. This multi-level contour integration yields a more accurate height distribution map, compensating for irregular geometries and asymmetric pile shapes.

Finally, the voxel-based volume computation discretizes the height profile into cubic voxels to approximate the total pile volume. The point cloud is voxelized using a user-defined voxel size (e.g., 0.1 m), grouping points into grid cells and counting occupied voxels at each height level. The script then sums the number of voxels multiplied by the cube of the voxel size to compute the volume, implementing optimizations to handle large datasets via sparse array representations. Voxelization ensures scalable and parallelizable computation, reducing memory overhead and enabling real-time processing for large stockpiles [6].

### 3.5 Validation Methodology

Validation and evaluation of results are crucial stages after developing an AI-based photogrammetry system to calculate bulk material volumes. Traditional methods of recording bulk material stocks are often inaccurate, especially when calculating the volume of irregularly shaped material piles. Aerial image-based photogrammetry is considered a more affordable alternative to LiDAR with good accuracy. The integration of AI (e.g., CNN) in image processing is expected to improve the accuracy of 3D models and volume calculations, as well as reduce manual errors. Therefore, validation steps are necessary to ensure that the system provides accurate and reliable volume results before being used in real-world applications.

#### 3.5.1 Validation Methodology

The validation methodology begins with the photogrammetric image processing workflow and ends with the evaluation of the output results. Image data from drones is processed through preprocessing stages, including video-to-image conversion, SIFT feature extraction, inter-image feature matching, and 3D structure reconstruction (SfM) to obtain point clouds and digital models (Digital Surface Model (DSM)/ Digital

Terrain Model (DTM)). The stockpile volume is then calculated from these 3D models. In the validation stage, the system is tested using field data (real data) that has been measured conventionally. The volume estimated by the photogrammetry-AI system is compared with manual measurements (ground truth) to assess the accuracy of the system. In addition, AI models such as Convolutional Neural Networks (CNN) or Mask R-CNN are used for automatic stockpile segmentation and pile contour feature detection. In several iterations, AI-based regression algorithms (Random Forest, XGBoost) were also applied to predict volume based on image features, in order to optimize prediction accuracy. The validation process included calculating error metrics (e.g., Root Mean Square (RMS) error, Mean Absolute Percentage Error (MAPE)) between predicted volume and manual results, as well as evaluating AI model performance under various material and flight conditions.

### 4. RESULT AND DISCUSSION

### 4.1 Testing Results and Performance Evaluation

Based on the Open Drone Map (ODM) report generated from processing the research dataset, a comprehensive evaluation of the accuracy and quality of 3D reconstruction showed excellent performance with an image reconstruction rate of 100% (199/199 shots) and a sparse point cloud reconstruction rate of 83.1% (119,424 out of 143,782 points). The system successfully generated a dense point cloud with 2,313,365 points and an average Ground Sampling Distance (GSD) of 0.1 cm, which indicates very high spatial resolution for stockpile volume measurement applications. The processing time of 23 minutes and 39 seconds shows good computational efficiency for a dataset of 199 images, in line with the OpenDroneMap benchmark for medium-scale UAV datasets [18]. Processing summary results can be seen in Table 1.

0	•
Metric	Value
Reconstructed Images	199/199 (100%)
Sparse Points Reconstructed	119,424/143,782 (83.1%)
Dense Points	2,313,365
Average GSD	0.1 cm
Detected Features	5,476
Reconstructed Features	2,881
Processing Time	23m:39s

**Table 1.** Processing Summary Results

The 100% image reconstruction rate indicates excellent dataset quality with adequate overlap between images. The sparse point reconstruction ratio of 83.1% is within the normal range for UAV photogrammetry, indicating good geometric consistency[19]. The dense point cloud with 2.3 million points provides very high surface detail for volumetric stockpile analysis.

		-	
Component	Mean (m)	Std Dev (m)	RMS Error (m)
X Error	-0.001	0.111	0.111
Y Error	-0.006	0.121	0.121
Z Error	0.001	0.550	0.550
Total 3D	0.062	0.275	0.282

Table 2. GPS Error Analysis

GPS error analysis in Table 2 shows excellent horizontal accuracy with RMS errors of 0.111~m and 0.121~m for X and Y, respectively, which are within the standard tolerance for UAV mapping without GCPs. However, the Z error of 0.550~m indicates the typical limitation of GPS in elevation measurement, which is still acceptable for preliminary volume estimation[20]. The mean bias, which is close to zero (-0.001, -0.006, 0.001), indicates that there is no significant systematic error in positioning.

Table 3. Accuracy Metrics Comparison

Component	Mean (m)	Std Dev (m)
Horizontal Accuracy CE90	0.208 m	0.209 m
Vertical Accuracy LE90	0.522 m	0.056 m
Average Reprojection Error (pixels)	0.57	0.19 (normalized)
Average Track Length	5.20 images	6.87 (>2 images)

In Table 3, the horizontal accuracy CE90 of 0.208 m meets American Society for Photogrammetry and Remote Sensing (ASPRS) standards for large-scale mapping, while the relative LE90 vertical accuracy (0.056 m) indicates excellent internal consistency. The average reprojection error of 0.57 pixels is within a good threshold (< 1 pixel) for photogrammetric reconstruction, indicating high-quality feature matching and

bundle adjustment convergence[21]. The average track length of 5.20 images indicates robust multi-view geometry, which is essential for accurate 3D reconstruction.

9,568

5,993

5,476

Statistic Minimum Maximum

Mean

Median

Detected	Reconstructed
4,074	274

5,334

3,119

2,881

**Table 4.** Feature Statistics

Feature detection statistics in Table 4 showing reasonable variance with an average of 5,993 detected features per image, which is sufficient for reliable photogrammetric processing. The average reconstruction rate of 52% (3,119/5,993) is within the normal range for SIFT features in UAV images, indicating good geometric consistency between views. The minimum number of reconstructed features of 274 per image is still sufficient for reliable camera pose estimation, while the maximum of 5,334 indicates rich texture content in some images (Fakhri et al., 2025).

#### 4.2 Validation Conclusion

The validation results demonstrate that the developed photogrammetric system achieved high accuracy, with a horizontal accuracy of 0.208 m and a reprojection error of 0.57 pixels, thereby meeting international standards for UAV-based photogrammetric mapping. The dense point cloud, consisting of approximately 2.3 million points with a GSD of 0.1 cm, provides a resolution that is highly adequate for accurate stockpile volume calculation. Furthermore, successful camera self-calibration and robust track distribution confirm the system's reliability for industrial applications in stockpile monitoring.

#### 5 CONCLUSION

The evaluation results demonstrate that the proposed AI-photogrammetry system effectively produces high-accuracy 3D models and reliable volume estimations of bulk material stockpiles. The implementation of this system in industrial environments can significantly reduce dependence on traditional manual measurement methods that are often prone to human error. Moreover, this photogrammetry-based approach offers a more affordable alternative to LiDAR, making it suitable for small- and medium-scale manufacturing operations. With its high spatial accuracy (CE90  $\approx 0.21$  m; LE90  $\approx 0.056$  m) and automated data-processing workflow, the system enhances operational efficiency in stockpile monitoring and raw-material management. These findings underscore the potential of integrating AI-driven photogrammetric analysis into digital manufacturing processes to support data-driven decision-making and sustainable resource utilization.

Based on these findings, the following recommendations are proposed for future work and development:

- 1. Employ additional machine learning algorithms (e.g., Random Forest, XGBoost) to further improve volume-estimation accuracy.
- Incorporate more GCPs or auxiliary sensors to enhance absolute georeferencing precision, particularly to minimize vertical bias.
- Conduct extensive testing under varying field conditions (different material types, camera angles, and weather scenarios) to ensure the robustness and generalization of AI and photogrammetry models.
- Integrate the developed system with Enterprise Resource Planning (ERP) or inventory-management platforms to enable real-time stock recording and improve supply-chain efficiency.

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