Comparative Evaluation of Classical and Deep Learning-Based 3D Reconstruction Methods via Web-Based Human Perception Assessment

Steven Bandong, Evan Christopher, Selvi Lukman, and I Wayan Palton Anuwiksa

***Abstract*—The rapid advancement of 3D reconstruction technology has created significant opportunities across various fields, yet its complexity remains a barrier to widespread adoption, particularly for novice users. This research evaluates and compares traditional and modern 3D reconstruction methods to assess their effectiveness in terms of reconstruction quality and processing efficiency. Classical approaches such as COLMAP and VisualSfM are analyzed alongside the neural network-based Instant-NGP to highlight their respective strengths and limitations. A comparative study is conducted based on both objective metrics and subjective human perception, ensuring a comprehensive evaluation of their performance. Additionally, user feedback is collected to assess ease of use and accessibility, providing insights into potential improvements for broader adoption. The findings indicate that modern deep learning-based approaches offer significant advantages in speed and flexibility, while classical methods retain strengths in accuracy and consistency. To facilitate access to 3D reconstruction frameworks and ensure a more reliable user evaluation, we also incorporate a web-based interface. This eliminates the need for users to manually collect data and execute reconstruction steps, allowing them to focus solely on evaluating the final 3D reconstruction results, thereby enhancing the validity of the user survey results.**

***Index Terms*—3D reconstruction, Neural radiance fields (NeRF), SFM+MVS, Triangulation.**

I. Introduction

THREE document dimensional (3D) modeling has gained significant traction across various industries, from entertainment to civil engineering [1]. Its primary advantage lies in its ability to reconstruct real-world objects into 3D digital counterparts, enabling intuitive visualization, manipulation, and supporting the burgeoning field of augmented reality (AR).

One approach used to achieve this is through photogrammetry technology [2]. Photogrammetry, a technique that extracts geometric information from 2D images to create 3D models of real-world objects, has emerged as a focal point in recent research [3]. Its key advantage is the ability to generate 3D models at a relatively low cost without the need for specialized equipment like LiDAR-based 3D scanners. Unlike LiDAR, which employs complex laser technology, photogrammetry utilizes affordable commercial cameras [4].

One photogrammetry technique that is being actively developed is Structure from Motion (SfM). Structure from Motion (SfM) is a prominent technique within photogrammetry and computer vision that reconstructs 3D structures from a sequence of 2D images captured from different viewpoints. By automatically identifying camera positions based on feature matching between images, SfM eliminates the need for manual calculations [5]. This advantage has led to the exploration of various open-source methods such as OpenSfM [6] and VisualSf [7]. Furthermore, COLMAP incorporates Multi-View Stereo (MVS) to produce dense 3D reconstruction surfaces [8]. With the advancement of AI, neural network-based methods like Instant NGP [9] have emerged, offering fast and dense 3D reconstructions compared to other neural network approaches.

This paper compares the strengths and weaknesses of both classical photogrammetry methods (OpenSfM, VisualSfM, and COLMAP) and the modern neural network approach (Instant NGP). We analyze their accuracy, completeness, realism, and computational time. Furthermore, to the best of the author's knowledge, there are few user interfaces that specifically address the challenge of making 3D reconstruction easily accessible to a broader audience. Most existing solutions require a significant level of expertise, which can be a barrier for novice users. In this paper, we present a user-friendly web interface designed to bridge this gap by simplifying the 3D reconstruction process. The interface not only streamlines the workflow but also incorporates a range of algorithms, allowing users to experiment with different techniques. The web interface is designed to streamline the process, making it more convenient and intuitive. Additionally, the interface not only simplifies the workflow but also integrates various algorithms, allowing users to experiment with different reconstruction techniques.

Manuscript received April 24, 2025. This work was supported in part by Calvin Institute of Technology under Grant LPPM-R-DR-2023-03-01-001-1

S. Bandong and E. Christopher are with Calvin Institute of Technology, Jakarta, Indonesia (corresponding author: S. Bandong, e-mail: steven.bandong@ calvin.ac.id).

S. Lukman, is with School of Computer Science and Computer Engineering Department, Universitas Bina Nusantara, Bandung, Indonesia

I. W. P. Anuwiksa is with Department of Data Science, Telkom University, Bandung, Indonesia.

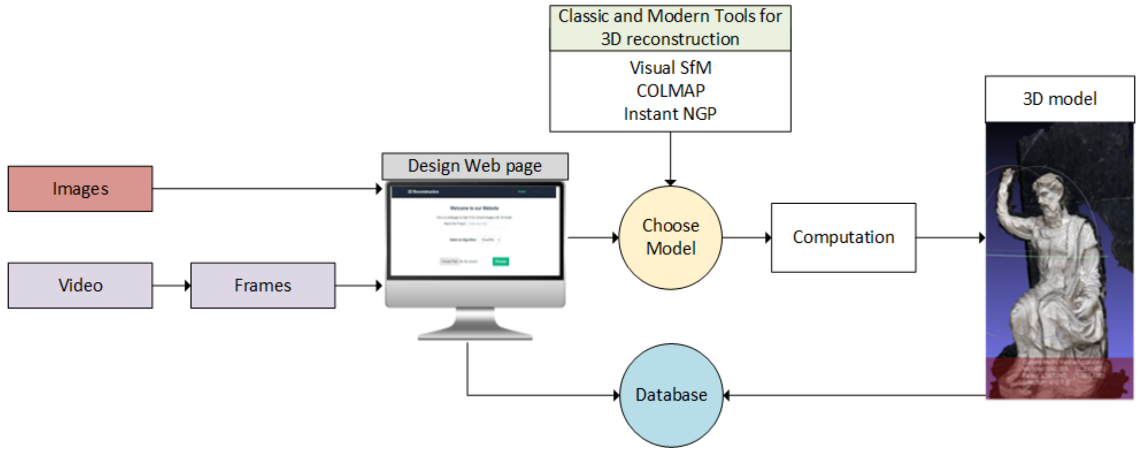

Fig. 1. Research Methodology.

II. Research Methods

The research is carried out in three main stages. The first stage involves exploring 3D reconstruction techniques, covering both traditional approaches and neural network methods. The second stage focuses on the development of a web interface for 3D reconstruction, while the final stage involves the evaluation methods used to assess the obtained results (See Fig. 1)

A. 3D reconstruction

The first step in this research methodology was selecting appropriate algorithms and software for 3D reconstruction. Four primary software packages were chosen: OpenSfM, COLMAP, VisualSfM, and Instant-NGP, based on their proven ability to transform 2D images into 3D models. Additionally, alternative options such as OpenMVG, OpenMVS, Bundler, MicMac, and Meshroom were considered. The study categorized the selected 3D reconstruction algorithms into two main groups: Classical AI-based algorithms: VisualSfM, OpenSfM, COLMAP and neural network-based algorithms: Instant NGP.

The dataset consisted of a series of 2D images, which could be obtained either from photographs or extracted from video frames of the object intended for reconstruction. The data collection process was conducted to ensure the availability of high-quality images with sufficient viewpoints to comprehensively capture the entire object. Subsequently, the selected algorithms were implemented. Each algorithm—OpenSfM, VisualSfM, COLMAP, and Instant NGP—was executed using the preprocessed data. This process involved configuring the algorithm parameters according to the research requirements.

The selection of an appropriate photogrammetry algorithm is essential for developing effective photogrammetry applications [10]. Numerous photogrammetry algorithms have been developed, each with its own strengths and limitations. For example, OpenSfM (Structure from Motion) is an efficient open-source framework for constructing 3D models from image collections by leveraging camera information and the relative motion between images [11].

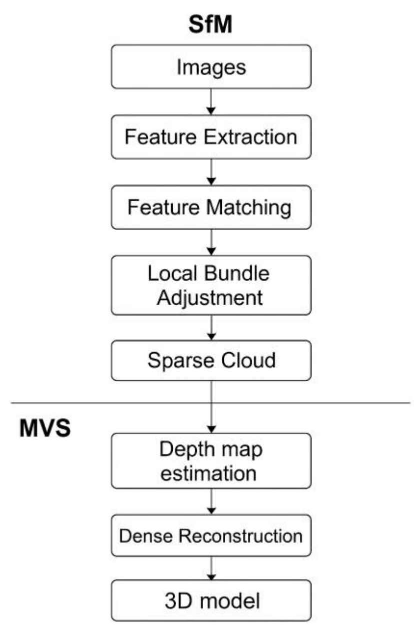

Fig. 2. Visual SfM flowchart.

VisualSfM (Visual Structure from Motion) is another widely used open-source algorithm for 3D reconstruction from images (see Fig. 2). The 3D reconstruction pipeline begins with image calibration, which corrects for lens distortions to ensure geometric accuracy in the subsequent processing steps. Following this, the Structure-from-Motion (SfM) process is initiated.Distinctive visual features such as corners, edges, and textures are extracted using Scale-Invariant Feature Transform (SIFT). This method identifies keypoints across scales using the Difference of Gaussian (DoG) function:

$$D(x, y, \sigma) = \big(G(x, y, k\sigma) * I(x, y)\big) - \big(G(x, y, \sigma) * I(x, y)\big) \quad (1)$$

here, L(x, y, σ) is the image blurred with a Gaussian kernel, where G(x, y, σ) is the Gaussian smoothing function, I(x, y) is the original image, and k is the scale factor controlling the degree of blur. These keypoints are matched across image pairs by computing the Euclidean distance between their descriptors:

$$d(A,B) = \sqrt{(\sum(A_i - B_i)^2)} \quad (2)$$

These correspondences enable the estimation of spatial relationships between images which enables the triangulation and bundle adjustment. Using the matched features, triangulation determines the 3D coordinates of points in space. Local bundle adjustment refines camera poses and 3D points incrementally for small sets of images. Global bundle adjustment then optimizes the entire reconstruction by minimizing reprojection error, ensuring higher accuracy and correcting drift. The result of SfM is a sparse point cloud representing the scene geometry and estimated camera positions.Multi-View Stereo (MVS) follows SfM to produce a high-fidelity 3D model. From the sparse reconstruction, MVS computes depth maps for each image using pixel-level photometric consistency. The individual depth maps are fused into a dense point cloud, capturing fine surface details. This dense cloud is then converted into a complete 3D model, typically represented as a mesh or textured surface [12].

COLMAP (see Fig. 3) is an advanced open-source 3D reconstruction pipeline that improves upon traditional methods like VisualSfM by integrating robust geometric verification and dense reconstruction techniques. After extracting features from images, it performs feature matching and applies geometric verification using the Fundamental Matrix constraint ($x'^{T}Fx = 0$) to ensure that only geometrically consistent matches are retained. This step, supported by RANSAC, eliminates outliers and prevents errors in triangulation and camera pose estimation. COLMAP also uses Homography Filtering to discard matches on planar surfaces, which could otherwise distort the 3D structure. Once verified, triangulation and bundle adjustment refine the camera positions and produce a sparse point cloud. In the MVS phase, COLMAP estimates and filters depth maps before fusing them into a mesh and applying texture, resulting in an accurate and detailed 3D model [13].

Instant Neural Graphics Primitives (Instant-NGP) (see Fig. 4) is a high-performance 3D reconstruction framework built on the Neural Radiance Fields (NeRF) architecture, designed for real-time training and rendering of 3D scenes [14]. The process begins with a set of input images, from which camera intrinsics, extrinsics, and sparse 3D points are extracted using COLMAP's Structure-from-Motion (SfM) pipeline. The sparse point cloud output from COLMAP is then converted into a format compatible with Instant-NGP, serving as the foundation for neural scene representation.

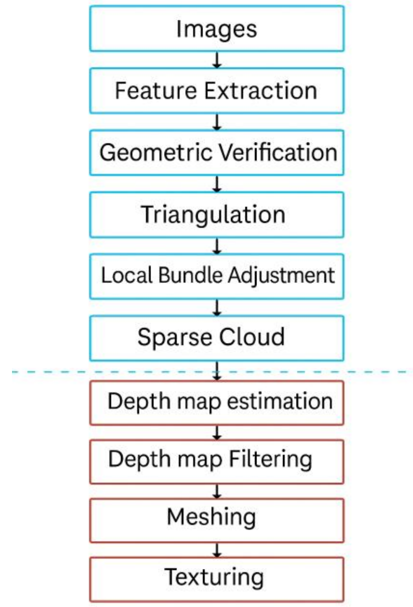

Fig. 3. COLMAP flowchart.

Once converted, Instant-NGP initiates training of a NeRF model using a multi-layer perceptron (MLP) architecture. The first step involves encoding 3D positions using a multi-resolution hash grid, which is a core innovation of Instant-NGP. This grid structure enables efficient and high-fidelity feature encoding across varying spatial scales, allowing the network to represent both fine-grained details and broader geometric structures. These encoded features are then passed through the first MLP to predict the volumetric density of each spatial location, along with latent feature vectors [15]..

Subsequently, a second MLP uses these features—along with view direction information—to predict the RGB color at each point. The predicted color and density values are accumulated via volume rendering, a differentiable process that synthesizes pixel intensities by integrating contributions along each camera ray. This rendering is compared to the actual pixel values in the training images, and the difference is measured using a photometric loss function (L_color). The network is trained iteratively using optimization techniques such as Stochastic Gradient Descent (SGD) and Adam, minimizing the loss until convergence.

Once training completes, the output is a continuous, fully learned Neural Radiance Field, which can be used to generate novel views of the scene from arbitrary camera angles. The efficiency of the hash grid encoding, combined with GPU-accelerated computation and optimized training, enables Instant-NGP to perform real-time or near-real-time 3D reconstruction—significantly faster than conventional NeRF implementations while maintaining high visual fidelity.

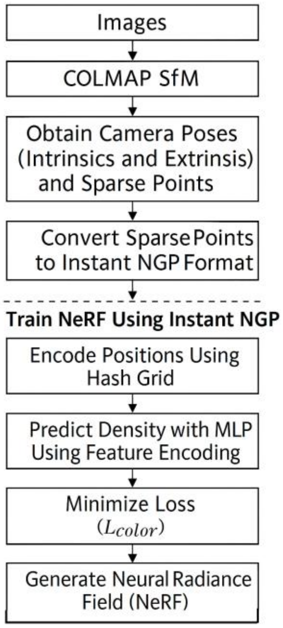

Fig. 4. Instant NGP flowchart.

B. Web development

This study presents a web-based application tailored for non-technical users to facilitate the generation of 3D models from image collections. The system features a Vue.js-powered front-end interface, designed to offer a responsive and user-friendly experience. The back-end, developed using the Flask framework, is responsible for data preprocessing, execution of reconstruction algorithms, and database operations, interfacing with an SQL-based database. For real-time, in-browser visualization of 3D models, the platform employs THREE.js, eliminating the need for additional software installations. Users can initiate model reconstruction by selecting a preferred algorithm and uploading a set of images. Upon processing, the backend generates a 3D model, which is rendered directly in the browser via THREE.js. The application also incorporates a model history feature, allowing users to access and download previously generated models in PLY format. Furthermore, an administrative dashboard is provided for efficient database management and monitoring.

C. Evaluation methods

Four evaluation methods were employed in this study. Firstly, a comparison between the number of images and the time required to generate a 3D model using VisualSfM was conducted. Secondly, the relationship between the number of images and the number of vertices produced using VisualSfM was examined. In both cases, the number of images refers to the different angles from which the object was captured. Graphs were generated to visualize the correlation between the number of images and processing time, as well as the number of images and the number of vertices produced. Thirdly, a comparison of the 3D reconstruction results from VisualSfM, OpenSfM, and COLMAP was performed. This involved comparing the generated 3D models and their corresponding processing times. The parameters of each algorithm were adjusted as needed to optimize performance.

Additionally, a survey was conducted with five participants to evaluate the 3D reconstruction results of three different objects: a mouse, a statue, and a pencil holder. The mouse represented a reflective object, the statue a large object, and the pencil holder an object with complex angles. Each object had four reconstruction results generated by the four different algorithms. Participants were asked to rate the reconstruction results on a scale of 1 to 5, with 1 being the lowest quality and 5 being the highest, based on four evaluation parameters: accuracy, completeness, smoothness, and noise level. The data collected from the survey was used for quantitative analysis to assess the performance of each 3D reconstruction algorithm. These evaluation methods provided comprehensive insights into the efficiency and effectiveness of different 3D reconstruction algorithms. Findings from both computational analysis and user evaluations contributed to a well-rounded assessment of reconstruction performance.

III. Results and Discussions

A. Web Page Development

As shown in the flowchart (Fig. 5), users begin by entering a project name or the name of the object to be converted from 2D to 3D. They then select an algorithm from the system's options—VisualSFM, COLMAP, or Instant NGP—and upload a set of images for processing. Upon clicking the 'Process' button, the system initiates the photogrammetry process using the chosen algorithm, employing state-of-the-art techniques. Once processing is complete, users are presented with a preview of the 3D reconstruction in the form of a point cloud. Users can interactively explore the 3D model using the built-in visualization tool integrated into the web interface, as shown in Fig. 6 (3D reconstruction results).

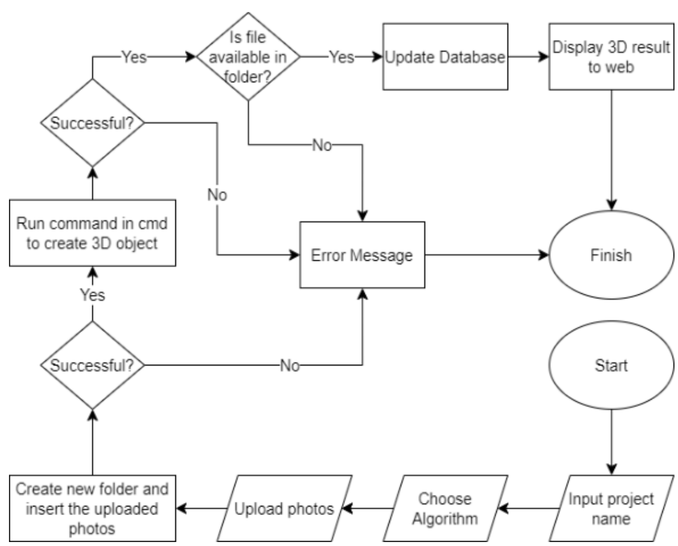

Fig. 5. Flowchart of the web page.

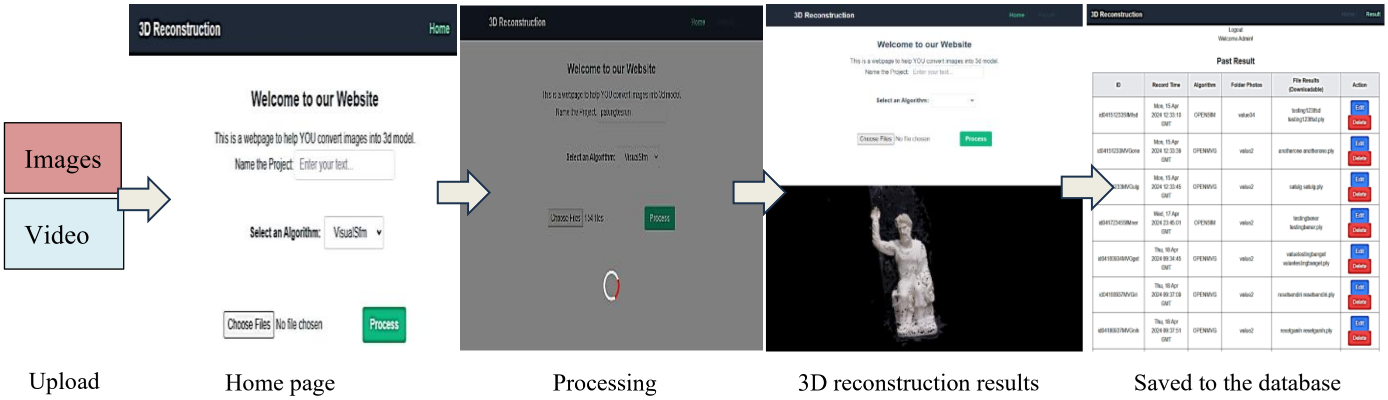

Fig. 6. Web page design result.

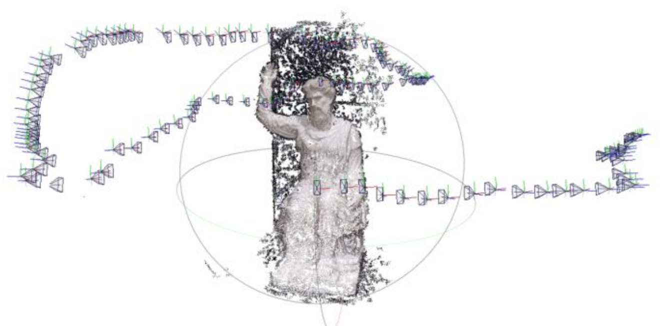

Fig. 7. The camera positions, illustrated as prismatic shapes, represent data collection points captured using a handheld smartphone. These positions were estimated through the auto-calibration feature in Structure-from-Motion (SfM).

Additionally, users can save the reconstruction results to the database. They may also download the 3D model in “ply” format for further inspection and manipulation using external software such as MeshLab or Blender. Fig. 6 displays the results of the web interface, following the workflow illustrated in Fig. 5. The process begins with the user uploading data in the form of an image series or a video, followed by processing, visualization of the reconstruction results, and the option to save the output to the database for future use or detailed examination.

B. *3D Reconstruction Evaluation*

The images—along with videos, which are converted into individual image frames—are processed using various 3D reconstruction algorithms. In this study, we evaluate three methods: VisualSfM, COLMAP, and Instant-NGP. VisualSfM and COLMAP represent classical photogrammetry-based approaches, whereas Instant-NGP employs a modern neural network-based technique. The output of the reconstruction differs significantly between these approaches. Traditional methods, such as VisualSfM and COLMAP, generate a set of 3D points (vertices) that form a sparse or dense point cloud. In contrast, Instant-NGP produces a NeRF (Neural Radiance Field) scene (Fig. 4).

A NeRF scene is a continuous volumetric representation of a 3D environment, learned from a set of input images using neural networks. Unlike traditional point clouds, NeRF encodes scene geometry and appearance by learning how light radiates from any point in 3D space given a viewing direction. This allows it to synthesize highly realistic novel views, making it particularly effective for rendering complex scenes with intricate lighting and surface details.

Due to the fundamentally different nature of the outputs, a direct quantitative comparison between traditional and neural network-based reconstruction methods is challenging. Consequently, this study focuses on comparing computation time and assessing reconstruction quality through human perception. This perceptual evaluation provides valuable insights by incorporating direct user feedback to assess key aspects of 3D reconstruction quality, including completeness, accuracy of detail, surface smoothness, and noise level.

In the initial stage, the reconstruction processes in VisualSfM, COLMAP, and Instant-NGP share a common procedure to estimate unknown camera positions. This begins with feature extraction and feature matching across multiple overlapping images. Through this process, Structure-from-Motion (SfM) techniques are applied to perform camera auto-calibration, which determines the camera poses relative to the object. The results of this auto-calibration are illustrated in Fig. 7, showing the estimated camera positions. The distribution of the inferred camera poses is non-uniform, primarily because the data was captured using a handheld smartphone. Unlike fixed or rig-mounted cameras, handheld capture introduces variability in viewpoint and motion, making accurate pose estimation more challenging due to the natural, dynamic movement of the user's hand during image acquisition.

Table 1 presents the results of reconstruction using VisualSfM, showing the relationship between the number of input images, processing time, and the number of vertices generated by the VisualSfM algorithm. As the number of input images increases, the number of generated vertices also tends to rise (with some exceptions). This indicates a positive correlation between the number of images and the complexity of the reconstructed model. However, it is important to note that a higher number of vertices does not always guarantee better reconstruction quality. As illustrated in Fig. 8—particularly in entries No. 8 (914 images) and No. 9 (1,827 images)—an excessive number of vertices can lead to noisy or inaccurate reconstructions.

Another significant observation is that the processing time required to generate the 3D model increases substantially as the number of input images grows. This exponential rise in processing time highlights the trade-off between the number of images used and the available computational resources.In conclusion, the results suggest that there is an optimal range for the number of input images that provides a balance between reconstruction quality, processing time, and computational cost. Further research is needed to determine this optimal number for different object shapes, levels of complexity, and desired reconstruction quality.

TABLE I
RECONSTRUCTION RESULTS, FRAME VS TIME VS VERTICES

No	Number of Images	Processing Time	Status	Vertices
1.	4	2 sec	No result	-
2.	7	2 sec	No result	-
3.	11	10 sec	Result not clear	7131
4.	21	22 sec	Half reconstruction	33368
5.	63	101 sec	Half unclear reconstruction	184331
6.	131	310 sec	Good	332964
7.	261	15 mins	Good	520776
8.	914	148.5 mins	Many noise	885222
9.	1827	534.3 mins	Full of noise	1403262

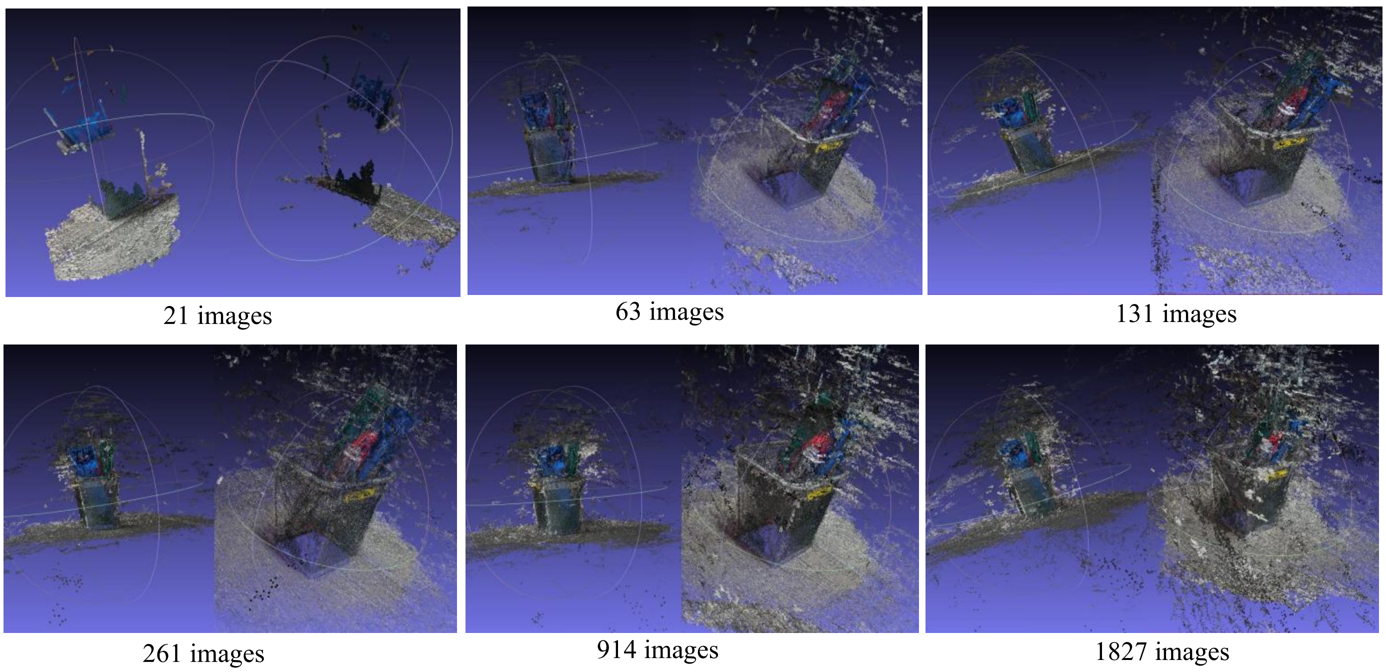

Fig. 8. The 3D reconstruction result corresponding to the data in Table 1, starting from entry No. 4 with 21 input images. Each image represents two viewpoints of the reconstructed 3D object. As the number of input images increases, the quality of the reconstruction generally improves. However, using too many images can also lead to noisy 3D object results.

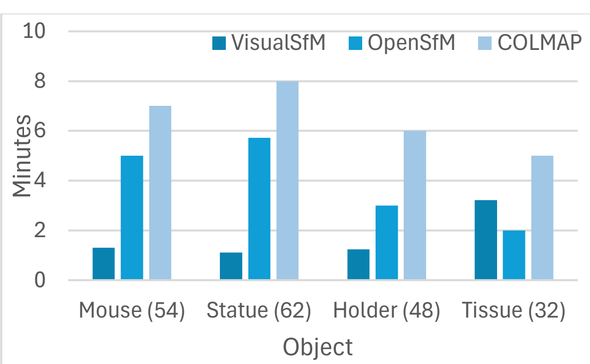

Fig. 9. Comparison of computation times for 3D reconstruction methods evaluated on various objects.

Further analysis is presented in Fig. 9, which demonstrates a consistent trend in processing time across the four tested objects using three different 3D reconstruction approaches. The numbers in brackets indicate the number of images processed by each algorithm. VisualSfM consistently outperformed the other algorithms, achieving the shortest processing times. OpenSfM ranked second in efficiency, while COLMAP showed the longest processing durations. Additionally, the processing time for all algorithms increased with the number of images processed. These findings suggest that VisualSfM's algorithmic design may be more computationally efficient than the others.

C. *Survey Evaluation*

This survey involved participants without specialized knowledge of 3D reconstruction, aiming to capture public perspectives and encourage a more inclusive evaluation of the reconstruction outcomes. The algorithms were assessed on three distinct object types: a reflective wireless mouse, a large statue, and a complexly angled pencil holder. A notable trend observed in Fig. 10.d is the consistently high performance of VisualSFM. Despite exhibiting lower scores in other metrics, VisualSFM produced reconstructions with minimal noise across all object types. This suggests that VisualSFM effectively handles image noise and outliers during the reconstruction process. In contrast, Instant-NGP demonstrated the highest noise levels, particularly for the statue and pencil holder, indicating potential challenges in handling complex scenes.

Regarding Fig. 10.a accuracy, Instant-NGP exhibited superior performance across all objects, surpassing the other algorithms by a significant margin. This suggests that Instant-NGP's neural network-based approach is highly effective in capturing fine details and geometric features. VisualSFM and OpenSfM showed comparable results, with slight variations across different object types. COLMAP, while generally performing well, exhibited lower accuracy for the complex pencil holder object, indicating potential limitations in handling intricate geometries.

In terms of Fig. 10.b smoothness, Instant-NGP again demonstrated exceptional performance, producing highly smooth reconstructions for all objects. This is likely attributed to the dense representation and interpolation capabilities of neural radiance fields. VisualSFM and OpenSfM showed similar levels of smoothness, with slight variations across objects. COLMAP, while generally producing acceptable results, exhibited some roughness in the reconstructions of the statue and pencil holder, suggesting potential challenges in surface interpolation.

Completeness Fig. 10.c, as measured by the extent to which the object is fully reconstructed, was generally high for all algorithms. However, Instant-NGP consistently achieved the highest completeness scores, indicating its ability to capture a larger portion of the object's geometry. VisualSFM and OpenSfM demonstrated comparable levels of completeness, with minor variations across objects. COLMAP showed slightly lower completeness for the complex pencil holder, potentially due to challenges in handling occlusions and self-similarities.

Instant-NGP exhibited the strongest overall performance across all evaluation metrics (Fig. 11), demonstrating its ability to generate high-quality, detailed, and complete 3D reconstructions. VisualSFM, while showing weaknesses in accuracy and completeness, excels in noise reduction and produces visually pleasing results. OpenSfM provides a solid balance of performance across different metrics. COLMAP, while competitive in certain aspects, shows limitations in handling complex geometries and noise.

These findings align with the notion that VisualSFM, despite its theoretical limitations in camera pose estimation, often produces visually appealing results due to its ability to suppress noise and generate smooth surfaces. However, for applications requiring high accuracy and completeness, Instant-NGP emerges as the preferred choice. Further research is needed to investigate the underlying factors contributing to the strengths and weaknesses of each algorithm and to explore potential hybrid approaches combining the advantages of different methods.

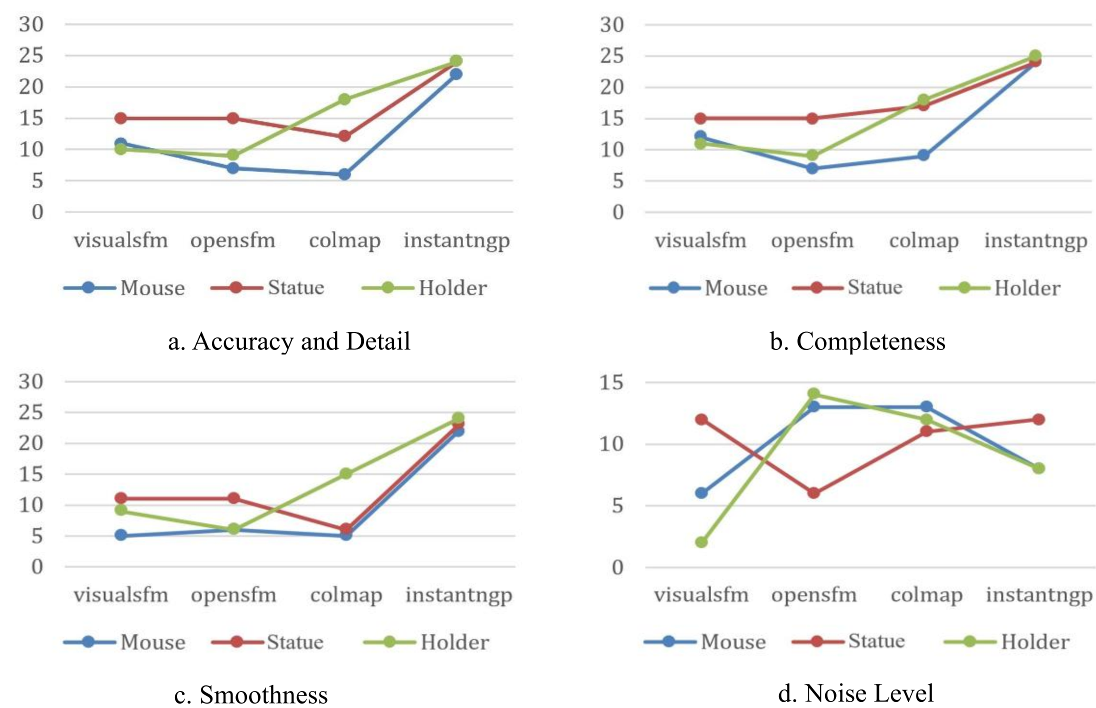

Fig. 10. Survey results reflecting human perception of the quality of 3D reconstruction outcomes.

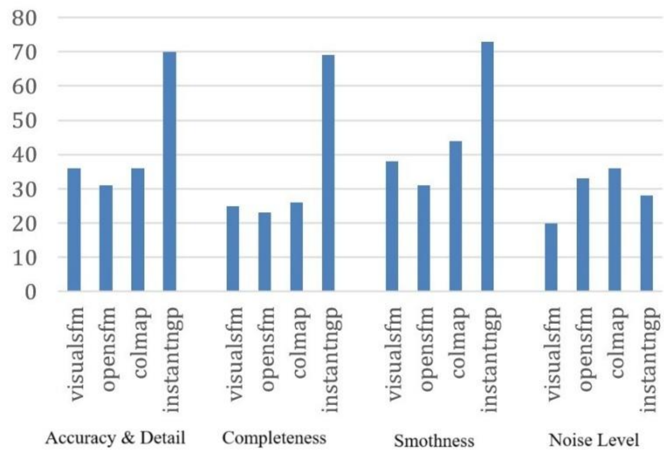

Fig. 11. Overall scores for each parameter.

IV. Conclusion

This research aimed to develop a web application capable of automatically generating 3D models from a collection of images, while also conducting a comparative analysis between traditional 3D reconstruction methods (based on vertices) and modern approaches utilizing deep learning (e.g., NeRF scenes). By integrating 3D reconstruction algorithms—including VisualSfM, OpenSfM, COLMAP, and Instant-NGP—the study successfully built a user-friendly platform for executing 3D reconstruction tasks. The comparison between the traditional algorithms (VisualSfM, OpenSfM, COLMAP) and the deep learning-based Instant-NGP revealed that the choice of algorithm is highly influenced by the characteristics of the target object. While Instant-NGP showed superior performance across various scenarios, VisualSfM remained the most efficient in terms of computation time. Overall, the developed web application offers an accessible and effective solution for users aiming to create 3D models without requiring in-depth technical expertise. As a future direction, this research could focus on optimizing algorithm performance for objects with low texture detail or those captured under challenging lighting conditions.

Data Availability

The data used in this paper are available at https://github.com/sbandong/IIJ_3Drec

Author's Contribution

Steven Bandong: Conceptualization, Methodology, Data Curation, and Analysis. Evan Christopher: Methodology, Data Curation, Writing – Original Draft, and Validation. Selvi Lukman: Supervision, Review, Validation, and Editing. I Wayan Palton Anuwiksa: Supervision, Review, and Editing.

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