Road Layer Detection and Volume Calculation Using UAV Technologies and Artificial Intelligence

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Abstract:

In traditional road construction monitoring, the methods commonly involve manual measurements and visual inspections, which are not only time-consuming but also prone to errors. To solve these problems, this study introduces an innovative method utilizing UAVs to capture high-resolution images of construction sites and a YOLO object detection model to identify different road layers from captured images. The drone-captured pictures help create detailed 3D maps, also known as dense point clouds. These maps are then used to measure the volume of the layers via four software applications to identify the most effective tool for UAV-based road layer analysis. The model is trained to identify different road layers from the images, allowing for precise segmentation. This new way of using drones and advanced software changes how road construction projects are managed. This method greatly improves how quickly and accurately we can monitor road construction, making it a big step forward in managing road projects.

Keywords:

Road Construction, YOLO, 3D Mapping, Drone technology, Aerial Road Survey

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1. Introduction

The traditional methods used in identifying the layers in the construction of roads and volume computation have been time-consuming. In the past, inspectors relied on physical measurements to make the necessary readings using a ruler and a measuring tape to determine the thickness of various layers of a road. Visual inspections were also crucial, as inspectors relied on what they could physically see to detail the state and progress of construction. Volume calculation and progress assessments in road construction have relied mainly on manual methods that use GNSS receivers and total station equipment as the main surveying instruments [1]. Precision was achieved in the total station by electronic distance measurement (EDM) together with angular measurements. However, these methods require significant time and manpower to control and read data, as well as interpret the outcome. Modern road construction projects require the highest level of accuracy when identifying road layers and calculating volume. The inefficiencies and inaccuracies of these traditional methods often lead to arguments and the loss of resources, such as money, time, and productivity, due to human error.

Technology advancements in recent years have demonstrated that they can increase the effectiveness and efficiency of construction operations. Artificial intelligence (AI) and photogrammetry are two technologies that have become significant tools with applications in various industries, including construction [2]. Using unmanned aerial vehicles (UAVs) on roads is a significant development. It allows for the capture of aerial photos to create high-resolution 3D models of construction sites, making volume calculations more efficient and precise compared to traditional surveying methods [3]. These photos make it easier to calculate the road layer volume precisely, enhancing construction quality. Furthermore, from extended training on various datasets from different sites, AI models improve detection accuracy, as demonstrated by the YOLO (you only look once) framework [4].

The YOLO framework has gained recognition in computer vision for its high accuracy and smaller model size[5]. It has seen several iterations over time, as seen in Figure 1, with each model improving in speed and accuracy. Many developers use YOLO models because they can be trained on a single GPU. Machine learning specialists can reasonably deploy these models on edge hardware or in the cloud [6]. YOLO’s architecture allows it to achieve high speed and efficiency, making it suitable for real-time processing applications, such as video surveillance [7]. YOLOv8, the most modern and sophisticated YOLO model, is appropriate for segmentation, object identification, and image classification [8]. Its architecture allows training on diverse datasets, ensuring remarkable performance across various scenarios [9]. The YOLOv8 model is anchor-free, meaning that instead of estimating an object's distance from a known anchor box, it directly guesses the object's center. By reducing the number of box predictions, anchor-free detection expedites nonmaximum suppression (NMS), a laborious postprocessing step that selects possible detections after inference [10]. YOLOv8 provides five models for identification, segmentation, and classification (YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x), with YOLOv8s being utilized for segmentation.

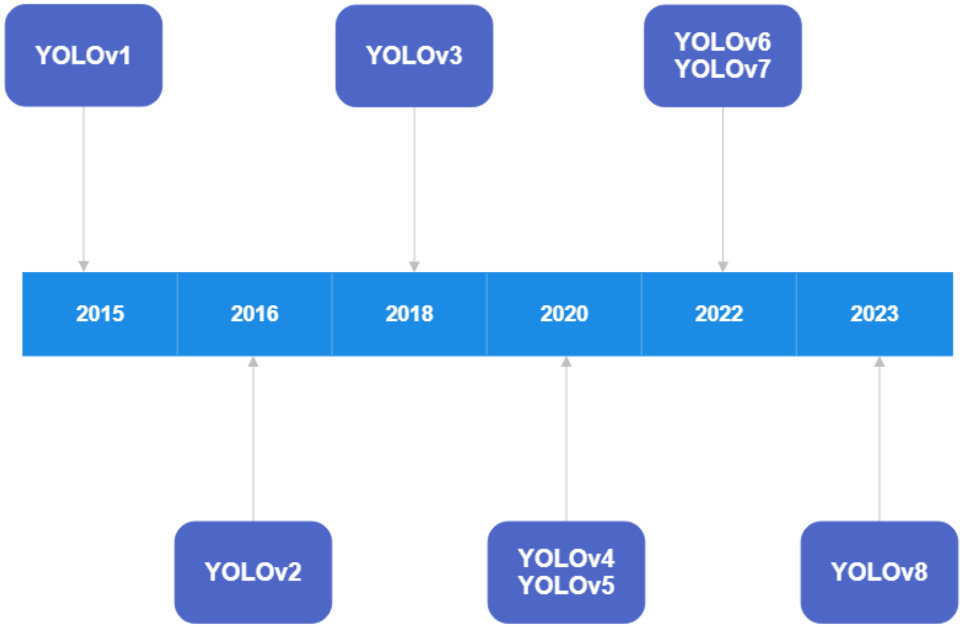


Figure 1: Timeline of YOLO models

Recent research has demonstrated the potential of UAVs and AI in infrastructure monitoring. The YOLOv5 target detection algorithm has demonstrated effectiveness in identifying road defects from UAV-captured images, showing significant potential in construction site monitoring [10]. Additionally, the combination of convolutional neural networks (CNNs) and Markov random fields (MRFs) has been employed to increase the accuracy of road defect detection by ensuring spatial consistency in feature extraction and classification [11]. UAVs equipped with LiDAR sensors have also been utilized to generate 3D point clouds, which are used for roadside object classification [12]. Moreover, several studies have focused on developing automatic point-cloud registration methods to improve quality control in construction projects [13] and on automatic progress monitoring, which can be improved by combining point-cloud maps with keymaps [14]. Change detection techniques using machine learning algorithms applied to UAV images have been developed to monitor the progress of road construction [15]. Semantic information for construction site monitoring can be combined with 3D change detection methods using UAV-based photogrammetric point clouds [16]. UAVs can also be used for earth calculations, and a method for measuring earth volumes, 3D modeling, and comparison measurements using vertical and oblique drone images has been proposed [17]. Transformed volumes, including 3D point clouds, have been investigated in many physical domains [18], especially in construction [19]. Finally, high-level data have been used for volume calculation via digital progress models [20], and semi-automatic drone-based systems have been explored to predict world activities [21] accurately. Various deep learning models, such as ARD-Unet, have shown promise in detecting cracks and other defects at the pixel level, thereby increasing the accuracy of infrastructure assessments [22].

This study suggests a novel approach to use the YOLOv8 model for road layer detection using images from construction sites. In this case, the segmentation model YOLOv8s-seg is used and is trained to identify and distinguish the road layers based on photographs taken by a drone. This is the first time that a YOLOv8 algorithm has been used for road layer segmentation. Additionally, dense point clouds are generated using the images captured to calculate the road layer volume using various software tools. By comparing the volumes obtained, the most effective approach is recommended.

2. Methodology

2.1 Detection Model

The process of training a detection model consists of 3 steps: (1) Data Collection, (2) Data processing, which involves data annotation and conversion, and (3) Model training.

2.1.1 Data Collection

High-quality overlapping photos of the road layer were taken with a DJI Phantom 4 Pro drone during the data collection, as seen in Figure 2a – Figure 2d. These photos, which included approximately 80% overlap, were taken at the Military College of Engineering construction site before and after the subgrade, asphalt, and aggregate base layers of the road were poured. Because every photograph is georeferenced, it provides coordinates for latitude, longitude, and altitude.

(a) (b)

(c) (d)

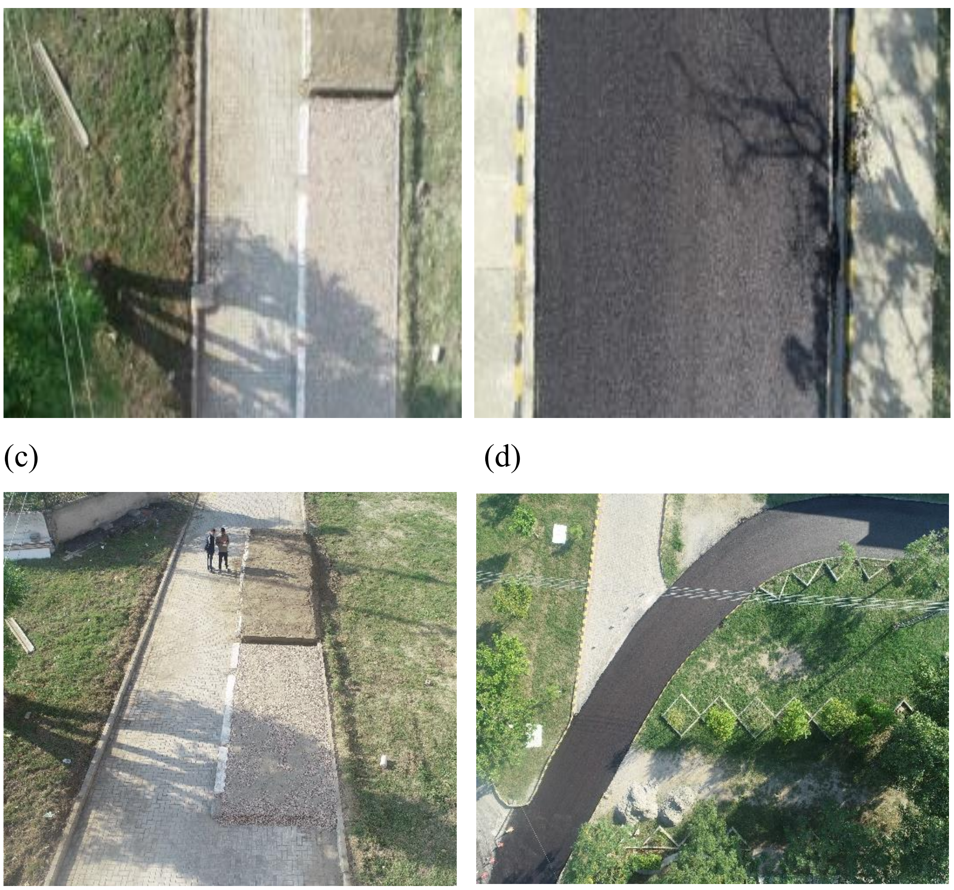


Figure 2: Data Collection

2.1.2 Data processing

The RGB images captured by the DJI Phantom 4 Pro were then processed in two steps to train the model.

i. Annotation

Annotation is a crucial step in the training of AI models, requiring precise labeling to guarantee that the models read data correctly. Accurate annotations are essential for building precise AI models. The images were annotated using the tool Labelme (see Figure 3). Over 1,000 images, including aerial views, front images, and side images of the road, were annotated to train the model.

ii. **Conversion**

The annotation procedure resulted in data saved in JSON files, which is incompatible with YOLO. Figure 4 illustrates the format that YOLO accepts. Using the tool labelme2yolo, the data was transformed into YOLO accepted format and was stored in text files.

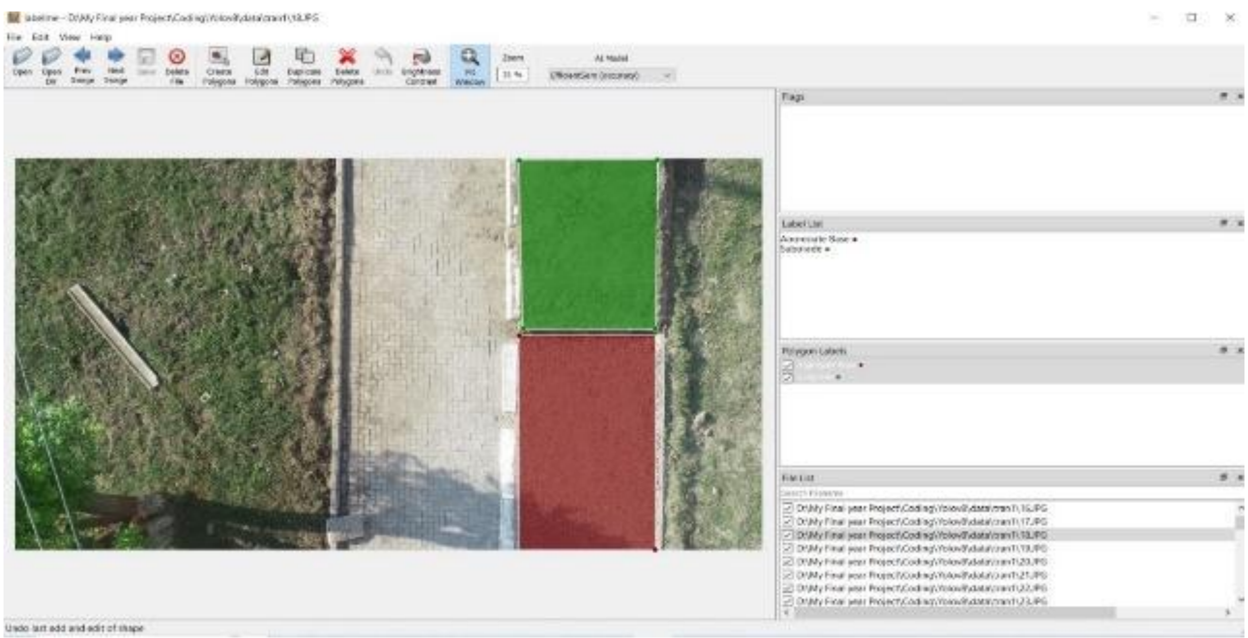


Figure 3: Annotation using labelme

Class x_center y_center width height

Figure 4: YOLO accepted format

2.1.3 Model Training

The YOLOv8 segmentation model was trained using annotated images after they were converted to a YOLO-compatible format. Google Colab was used for training, as it provides access to a GPU, making it easier to manage processing demands. The model was trained for 400 epochs using a

1024 image size and a batch size 8. The dataset was split into 70%-training and 30%-validation to assess the model correctly. At the beginning of the training, the model showed high classification loss, segmentation loss, and box loss. This includes metrics for predicting the correct classes, object segmentations, and bounding box locations. However, as the training progressed, these losses gradually decreased with each epoch. This steady reduction in loss values demonstrated that the model was learning and improving its ability to interpret and segment the images accurately. Regular checkpoints were saved during training to monitor the model's progress and prevent overfitting. Early stopping criteria were also set to halt training if the validation loss stopped improving.

2.2 Volume Calculation

The process of volume calculation consists of 3 steps. There is (1) Data Collection, (2) Dense point cloud generation, and **(3)** Volume calculation using four different software.

2.2.1 Data Collection

The RGB images captured by the drone for the YOLO model were also used for volume calculation. These images were explicitly taken with dual purposes in mind: layer detection and volume calculation. To ensure accuracy, ground control points (GCPs) which are visible in the images, were marked at the site. This step was necessary because the GPS coordinates embedded in the images were not sufficiently precise, and relying solely on them would have resulted in significant errors. The GCP can be seen in Figure 5 as a yellow mark.

Figure 5: GCP marked in Yellow color

2.2.2 Dense Point Cloud

Using Agisoft Metashape, point clouds were generated from the RGB images of the site through photogrammetric reconstruction before and after the layer was laid. This process included aggregating images to create a model that depicted the road surface in 3D form. GCPs were also crucial for the proper orientation of the point cloud to the real-world coordinates; thus, they played a significant role in the georeferencing process. After achieving accurate georeferencing, the point cloud was again post-processed to create a dense point cloud. This gave a highly dense and comprehensive road surface point cloud map. Figure 6 illustrates the dense point cloud before the layers were laid, while Figure 7 illustrates the dense point cloud after laying the layers.

Figure 6: Dense point cloud before construction

Figure 7: Dense point cloud after construction

2.2.3 Volume Calculation

The dense point clouds created by Agisoft Metashape were used to determine the volume of the road layers. The software tools employed for volume calculation included Agisoft Metashape, CloudCompare, Civil 3D, and WebODM.

2.2.3.1 Agisoft Metashape:

In Agisoft Metashape, polygons were drawn around the boundaries of each road layer, the subgrade layer, the aggregate base, and the asphalt (see Figure 8a—Figure 8c). These boundaries were established to obtain the correct volume of each layer. After the layer boundaries were set, the software calculated the volume of each layer with regard to elevation variation within these polygons. This way, more accurate estimations of the volume of each layer were achieved with reference to the detailed 3D models obtained from the dense point clouds.

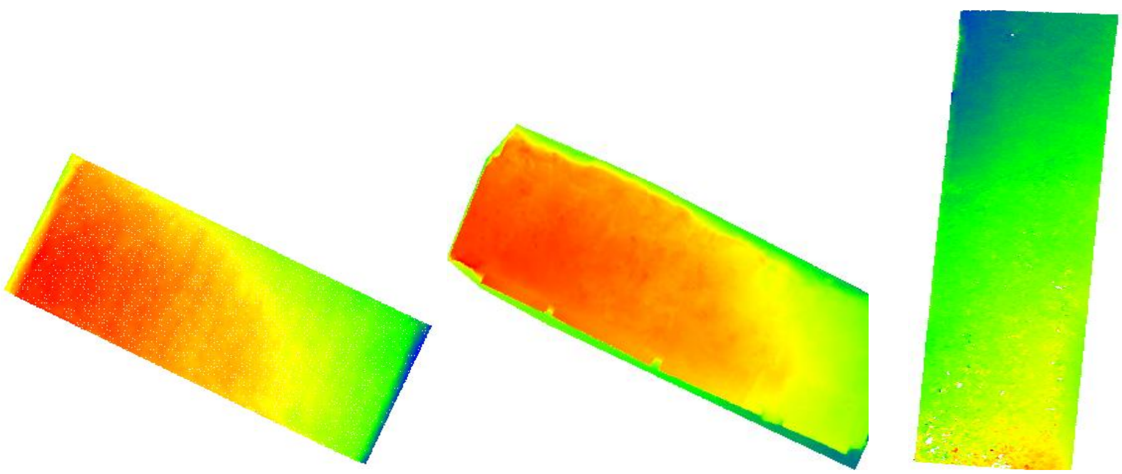
Figure 8: Polygon Boundaries around Aggregate Base, Subgrade and Asphalt

(a) (b) (c)

2.2.3.2 CloudCompare:

In CloudCompare, the volume calculation process involved cropping the area of interest (layer) from the dense point cloud obtained from Agisoft Metashape (see Figures 9a—9c). This approach allowed for an accurate measurement of the volume of materials used.

Figure 9: Cropped Aggregate Base, Subgrade and Asphalt



(a) (b) (c)

2.2.3.3 Civil 3D:

In Civil 3D software, the generated dense point clouds before and after construction were uploaded. By importing the point clouds, surfaces were created for the respective stages of the construction progression. This involved the generation of TIN (Triangular Irregular Network] surfaces by the elevation obtained from the point clouds. The pre and post-construction surfaces of similar layers were placed over each other to get a view of the changes that took place during the construction phase, see Figure 10a – 10c. The volumes of each layer of the pre and post-construction, subgrade, aggregate base, and asphalt were determined. Any variation or difference in the volume ascertained the amount of material added or removed during construction.

(a) (b) (c)

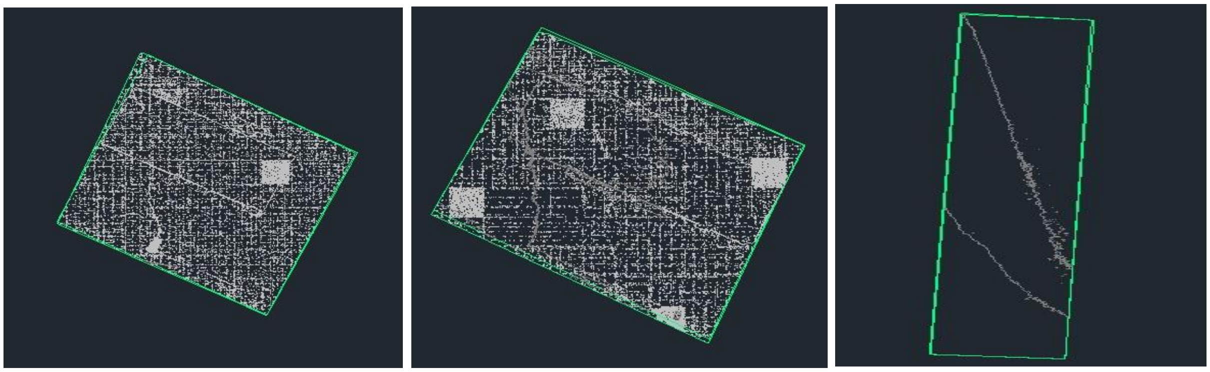


Figure 10: Overlapped Surface of Aggregate Base, Subgrade and Asphalt before and after construction

2.2.3.4 WebODM:

WebODM (Web Open Drone Map) was employed to estimate the volume of road layers based on its highly efficient photogrammetry processing module. The following steps were involved in this process:

- The different RGB images taken with the drone were then shared in WebODM, which converted the images into a 3D model of the construction site. This produced an orthophoto and a dense point cloud from the given images.
- GCPs were used in the WebODM process to increase the accuracy of the 3D model. These points provided accurate geographical location, orienting the model according to actual coordinates so that the volumetric calculations are highly accurate.
- Within WebODM, a cube or a curve was placed over the processed point cloud to define the boundaries of the road layers. The software then calculated the volume based on the elevation data within these defined boundaries. WebODM's usability also enabled navigation and the modification of cubes or curves in a very straightforward manner, allowing for accurate adjustment of road layer boundaries.

3. Results and Discussion

3.1 Detection Model

When the model was trained for 400 epochs, a graph was created depicting the box, classification, and segmentation loss see Figure 11 below. The loss value for the trained model declined over the epochs, proving that the model was being trained effectively. Still, it was noted that the overall loss values were still quite high even after the training was completed. This could be because the points used during the annotation process were so numerous as required for the segmentation of the layers and might have added difficulty or complexity in modeling the segmentation boundaries.

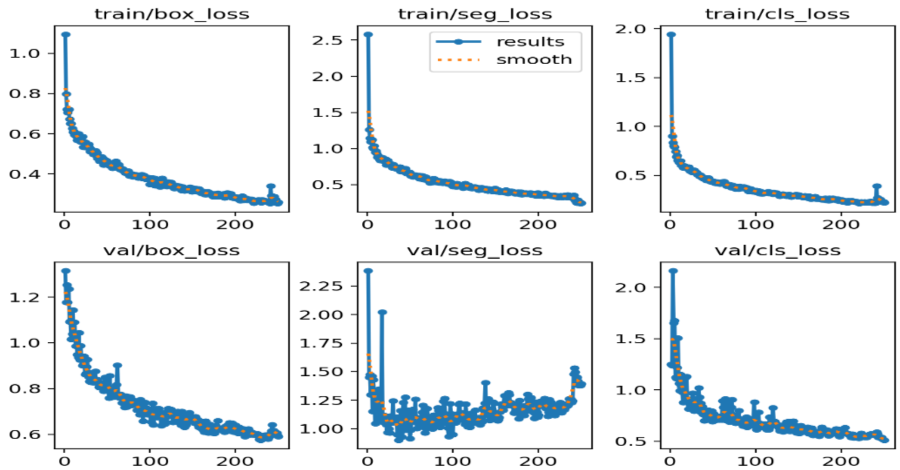


Figure 11: Training and validation Loss

The trained model was subsequently used to predict on images of the site that were not included in the training set and were entirely unseen by the model. The detection responses for the subgrade and aggregate base are presented in Figure 12a – 12b, while the detection result for the asphalt is depicted in Figure 13a – 13b. The detection result for random images is shown in Figure 14a – 14b.

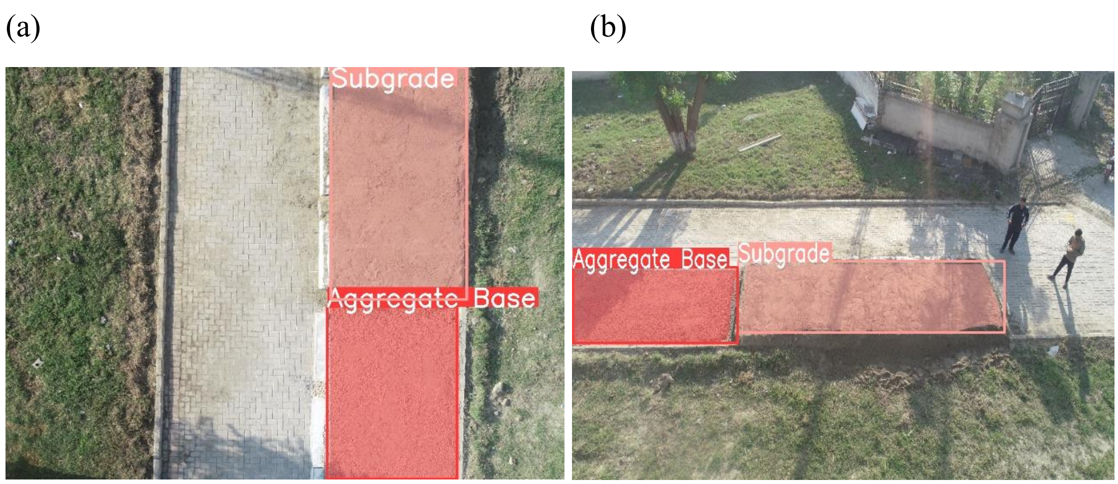


Figure 12: Detection results of aggregate base and subgrade layer

(a) (b)

Figure 13: Detection results of Asphalt layer

(a) (b)

Figure 14: Detection results

3.2 Volume Calculation

To assess the accuracy and reliability of these software tools, the calculated subgrade volumes from Agisoft Metashape, CloudCompare, Civil 3D, and Web ODM were compared with the actual volume laid on the site (see Table 1).

Table 1: Comparison of Subgrade Volume

Software	Calculated Volume (m^3)	Actual Volume (m^3)	% Accurate
Agisoft Metashape	**4.731**	**4.59**	**96.93%**
Cloud Compare	**4.636**		**98.99%**
Civil 3D	**4.75**		**96.51%**
Web ODM	**4.597**		**99.85%**

The calculated aggregate base volumes from Agisoft Metashape, CloudCompare, Civil 3D, and Web ODM were compared with the actual volume laid on the site to assess the accuracy and reliability of these software tools, see Table 2.

Table 2: Comparison of Aggregate Base Volume

Software	Calculated Volume (m^3)	Actual Volume (m^3)	% Accurate
Agisoft Metashape	**2.426**	**2.26**	**92.65%**
Cloud Compare	**2.395**		**94.03%**
Civil 3D	**2.63**		**83.62%**
Web ODM	**2.262**		**99.9 %**

The calculated **asphalt** volumes from Agisoft Metashape, CloudCompare, Civil 3D, and Web ODM were compared with the actual volume laid on the site to assess the accuracy and reliability of these software tools, see Table 3.

Table 3: Comparison of Asphalt Volume

Software	Calculated Volume (m^3)	Actual Volume (m^3)	% Accurate
Agisoft Metashape	**8.083**	**8.17**	**98.93%**
Cloud Compare	**8.916**		**90.86%**
Civil 3D	**9.37**		**85.31%**
Web ODM	**8.182**		**99.85%**

The comparison of calculated and actual volumes using different software tools highlights the varying degrees of accuracy achieved by each method. The evaluations indicated that WebODM was the most accurate, and Agisoft Metashape and CloudCompare were second most accurate compared to Civil 3D. These results also indicate that WebODM outperforms other methods in terms of volume calculations, suggesting its potential as a preferred tool for precise and reliable calculations in road construction projects using UAVs.

4. Conclusion

This research is a breakthrough in road construction and supervision using UAV Technologies and AI. The greatest finding of this work is that, through this study, a YOLOv8 model was trained and used to detect road layers on its own, which is the first in the field. The high-resolution images obtained via UAVs were helpful in generating dense point clouds, which in turn helped in the accurate computation of the volume of road layers.

By employing four different software tools, including Agisoft Metashape, CloudCompare, Civil 3D, and WebODM, we assessed the accuracy of volume calculations for subgrade, aggregate base, and asphalt layers. Our study observed that the overall accuracy given by WebODM was the highest among all layers tested, with an accuracy level of 99.85% for subgrade, 99.9% for aggregate base, and 99.85% for asphalt. This makes WebODM the most suitable tool for estimating road construction project volumes. The implications of this research are profound. The integration of UAVs and AI not only enhances the precision of road layer measurements but also significantly reduces the time and labor required for such tasks because the time spent on manual inspections and calculations will be reduced, as well as the number of surveyors on-site. This approach minimizes human error, enhances data security, and ensures consistent construction progress monitoring. As a result, adopting these technologies can lead to improved project management, cost savings, and better road construction quality.

From this research emerge several additional questions and avenues for future investigation. Another area that needs further development is the existing YOLO model, which can be upgraded to detect and analyze even further aspects of road construction. Although in this paper we have presented and analyzed only three major layers: subgrade layer, aggregate base course, and asphalt course, road construction, in reality, involves more layers and can have a more elaborate structure. It should be noted that training to recognize and segment additional layers might improve the created model as a more comprehensive tool for monitoring.

Moreover, with further research, a model or tool that would take images as input, generate dense point clouds, select the area of interest, and calculate the volume could be suggested. This advancement would reduce the number of applications used to carry out the process by combining them into one comprehensive application. Such a model holds the potential for high efficiency and effectiveness in handling larger construction projects without much interference from human operators.

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