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Article

Drone-based pothole detection and sustainable repairs

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Abstract: Potholes are one of the major challenges affecting road safety, vehicle performance, and infrastructure maintenance worldwide. Conventional pothole detection and repair methods are often time-consuming, labour-intensive, and inefficient in large road networks. Recent advances in drone technology and geospatial data processing provide new opportunities for rapid and accurate road condition assessment. However, limited research integrates drone-based detection with sustainable repair material evaluation. This study proposes a drone-based pothole detection framework combined with a sustainability-oriented repair analysis. A UAV survey was conducted using the DJI Mavic 3 Enterprise to capture high-resolution images of road surfaces. The collected imagery was processed using photogrammetry software such as Agisoft Metashape and QGIS to generate orthomosaic images, digital elevation models (DEM), and pothole measurements. The calculated pothole area and volume values obtained through software were compared with manual measurements, showing a high accuracy range of approximately 97–99%. In addition, a comparative cost analysis of conventional repair materials and sustainable alternatives, including coconut shell charcoal, rice husk ash, HDPE plastic, and demolished aggregates, was performed. The results indicate that sustainable materials can reduce repair costs by up to 13.43%, while drone-based surveys significantly reduce inspection time and improve monitoring efficiency. The proposed integrated approach demonstrates the potential of combining UAV-based infrastructure monitoring with environmentally sustainable repair strategies. This framework can support smarter road maintenance planning and contribute to sustainable infrastructure management.

Keywords: pothole detection; drone technology; road safety; unmanned aerial vehicles; sustainability

1. Introduction

Roads are an essential mode of transport. Road transport accounts for a significant share of a country's passenger traffic. Road infrastructure is the backbone of society's development, used to accommodate economic activity and daily business. However, the ubiquitous problem of potholes causes serious issues, including damage to cars, safety threats, and higher maintenance costs. Due to inadequate maintenance, poor road surface quality, or other factors, potholes can develop on roads. A pothole is a type of surface disruption of a road where a piece of road material is damaged. During rainy periods, if such potholes fill with water, they may cause accidents that can even be fatal. Monitoring potholes across large road networks remains challenging for authorities. The conventional process of pothole detection and repair involves the use of conventional materials.

Along with urbanization, there is a severe need to find innovative and efficient solutions for maintaining the roads in a sustainable manner. Recent developments in technology have led to the introduction of Unmanned Aerial Vehicles (UAVs), also known as drones, along with deep learning algorithms for pothole detection. Unmanned Aerial Vehicles (UAVs) have the potential to cover large areas and take high-resolution images at a reasonable cost. These images can then be used to detect potholes on the road and quantify their dimensions. Unmanned Aerial Vehicles (UAVs) have the potential to utilize deep learning algorithms to detect potholes on the road. This has the potential to increase the efficiency of road maintenance services. Studies on the utilization of sustainable materials for pothole repair have gained momentum. Studies on the utilization of sustainable materials such as coconut shell charcoal, recycled materials, HDPE Plastic, and Rice-husk Ash for pothole repair have the potential to be used as alternatives to conventional materials.

These materials are environmentally sustainable while offering comparable durability to conventional materials. This study integrates drone-based pothole-detection technology with sustainable repair materials and analyzes their economic viability. Despite significant advancements in UAV-based road monitoring and sustainable pavement materials, most existing studies address these aspects separately. Many studies focus on automated pothole detection using computer vision and drone imagery, while others examine sustainable materials for pavement repair. However, there is limited research that integrates drone-based pothole detection with quantitative analysis of repair requirements and cost-effective, sustainable repair materials. Furthermore, practical comparisons between drone-based measurement methods and conventional manual approaches remain limited in real field conditions. Therefore, this study aims to bridge this gap by integrating UAV-based pothole detection, geospatial analysis, and cost evaluation of sustainable repair materials.

2. Related work

Effective pothole detection and road maintenance management systems play a critical role in improving road safety and optimizing infrastructure efficiency. GIS-based pavement management systems have been widely adopted for monitoring and prioritizing maintenance activities [1]. The integration of GIS databases further enhances the accuracy of road surface monitoring and supports informed decision-making in infrastructure asset management [2]. Advances in non-destructive testing and instrumentation techniques have significantly improved the assessment of pavement conditions and performance [3].

Recent developments in Unmanned Aerial Vehicle (UAV) technology have demonstrated substantial potential for road surface evaluation. UAV-based profiling techniques offer improved efficiency and coverage compared with conventional survey methods [4]. In addition, computer vision and deep learning approaches integrated with UAV imagery have enabled automated pothole detection and road damage assessment with high accuracy [5–9]. Data-driven approaches are also increasingly being used to enhance infrastructure monitoring and enable intelligent decision-making processes [10].

UAV-based photogrammetry and structure-from-motion (SfM) techniques have been widely used for accurate 3D reconstruction and terrain modelling. These methods enable precise measurement of surface irregularities such as potholes through the generation of orthomosaic images and digital elevation models (DEM) [11–14]. Such techniques provide reliable and scalable solutions for infrastructure inspection and analysis.

Digital Twin (DT) technology is emerging as a promising approach for infrastructure lifecycle management. DT frameworks provide intelligent decision-support systems for maintenance planning and operational monitoring [15]. The integration of multi-domain data further improves the efficiency of infrastructure operations and maintenance processes [16]. Several studies have highlighted the application of digital twin technologies in civil infrastructure, emphasizing their role in enhancing infrastructure intelligence and management [17, 18]. Lifecycle-oriented digital twin models have also been developed for transportation systems, particularly for highways and linear infrastructure [19]. Furthermore, the integration of Building Information Modeling (BIM) with digital technologies improves the planning and analysis of maintenance activities [20].

From an economic and sustainability perspective, the long-term effectiveness of pothole repair techniques has been widely investigated. Optimized pothole patching methods have been shown to improve pavement durability and reduce maintenance costs [21]. Advanced repair techniques, such as preheating methods, have demonstrated improved performance in pothole rehabilitation [22]. The use of reclaimed and recycled materials has gained attention as an effective strategy to reduce the consumption of virgin resources and lower repair costs [23–27]. Analytical models based on pavement deterioration have also been proposed to enhance lifecycle performance and sustainability [28].

Moreover, geospatial and remote sensing techniques have been increasingly applied to infrastructure monitoring and environmental assessment, contributing to sustainable infrastructure development [29]. GIS-based frameworks also support sustainable urban mobility planning and efficient infrastructure management [30]. Recent studies emphasize the use of waste-based materials such as plastic waste, agricultural residues, and recycled asphalt to improve pavement sustainability while reducing environmental impacts [31].

3. Research methodology

3.1. Data collection

Data for this study were collected through a comprehensive literature review. The review focused on recent applications of drones in construction, safety monitoring, and infrastructure management. A total of 22 pothole samples were selected using a random sampling approach across the study area. The sampling ensured variability in pothole size and depth. Assumptions used in calculations include:

- Grid size for manual measurement: 10 cm × 10 cm;
- DEM base level defined using the surrounding road elevation;

- Contour interval selected based on the resolution of the DEM.

3.2. Problem recognition

The collected data were analysed to identify potential challenges and research gaps in implementing drones in the infrastructure industry for monitoring, inspection for repairs, and possible integration with other digital technologies. From the shortlisted problems, Road Pothole Detection and Cost Analysis for Pothole Repair Using Sustainable Materials was chosen for this study.

3.3. Research design

This study employed a mixed-methods approach combining qualitative and quantitative data collection techniques. The overall research framework integrates UAV-based data acquisition, photogrammetric processing, pothole quantification, statistical validation, and cost-based sustainability analysis, ensuring a systematic and reproducible workflow.

A schematic flowchart of the research methodology is presented in **Figure 1**. The workflow includes five major stages: (i) UAV-based data acquisition, (ii) photogrammetric processing using Agisoft Metashape, (iii) pothole quantification using DEM and orthomosaic analysis in QGIS, (iv) statistical validation through MAE, RMSE, and R^2 metrics, and (v) economic and sustainability analysis of repair materials. This structured framework ensures reproducibility and clarity of the research process.

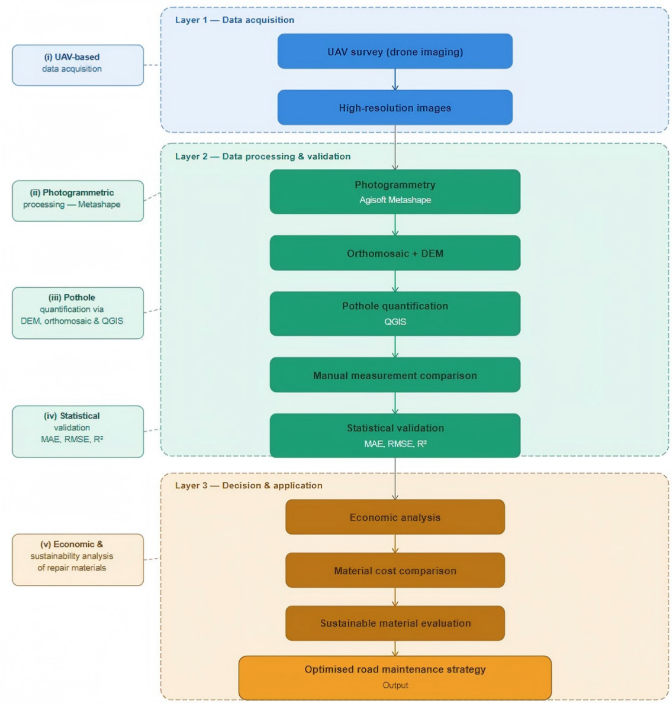


Figure 1. Integrated framework for UAV-based pothole detection and sustainable repair analysis.

3.3.1. Drone selection

When selecting a drone for surveying, consider factors such as payload capacity, flight time, and stability. The size of the survey area, the type of camera required, and your budget will impact your choice of drone. The drone selected for this study is the DJI Mavic 3 Enterprise.

3.3.2. Data acquisition

Drone aerial photography must be carefully planned and executed accurately. The exercise begins with navigating through the pre-planned flight path and camera and GPS calibration for effective data capture. As shown in **Figure 2**, once the drone was installed and in autonomous mode, it flies a pre-planned route while the operator configures camera parameters based on site conditions, such as white balance and shutter speed, to produce high-quality images. Live video and telemetry data, including altitude, battery level, and GPS signal strength, are monitored in real time during flight. Images are captured every one second with 80% overlap to generate seamless stitching for orthomosaic and 3D models. Flying at 40 m above ground, the team periodically checks image quality and resolution. After the flight, the data is carefully analysed on a large screen to ensure that any faults not apparent in the field have been captured and that all images are correctly tagged with associated metadata for easy retrieval. This systematic, precise approach delivers accurate, reliable results for mapping and survey work.

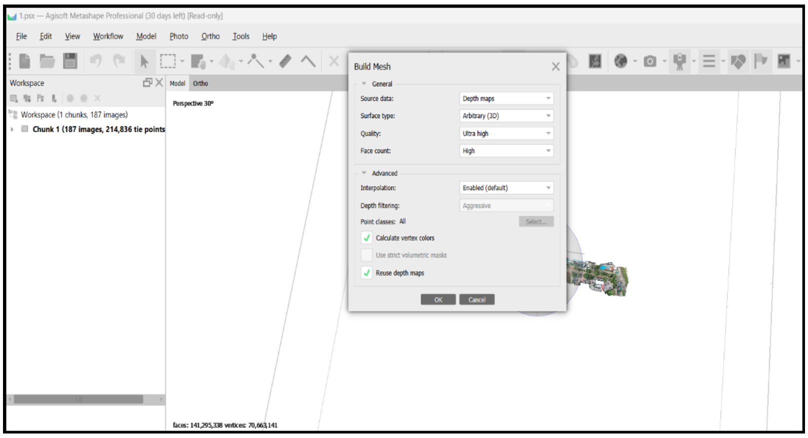
Figure 2. Drone captured image.

3.3.3. Data processing

Data processing is carried out using Agisoft Metashape software, which provides the data in the following formats:

Agisoft Metashape: It is a photogrammetry software used to process drone imagery to generate high-resolution, accurate 3D models and orthomosaics. In this project, images were processed to detect and analyse potholes on road surfaces.

1. **Data import and pre-processing:** The images are typically captured at high resolution and low altitude to capture detailed road surface texture.
2. **Photo alignment and sparse point cloud generation:** In this process, as shown in **Figures 3** and **4**, Agisoft Metashape creates a sparse point cloud, which is basically a 3D outline representing the survey area that establishes the relative position of each image by aligning them based on visual similarity as well as GPS metadata for accurate coverage of the road surface.

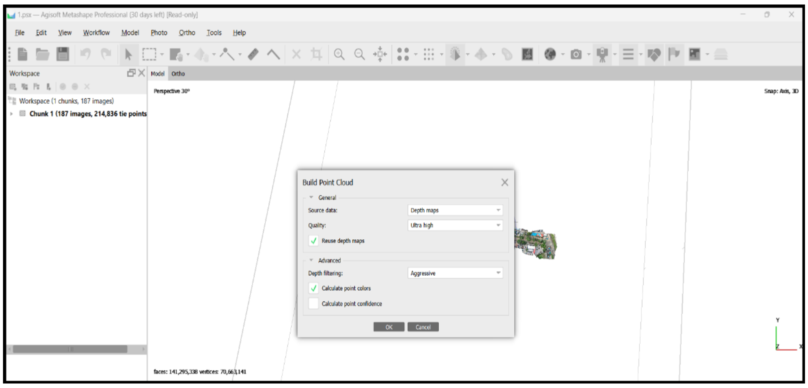


Workspace (1 chunks, 187 images)
Chunk 1 (187 images, 214,836 tie points

Build Mesh
General
Source data: Depth maps
Surface type: Arbitrary (3D)
Quality: Ultra high
Face count: High
Advanced
Interpolation: Enabled (default)
Depth filtering: Aggressive
Point classes: All
☑ Calculate vertex colors
☐ Use strict volumetric masks
☑ Reuse depth maps

faces: 141,295,338 vertices: 70,663,141

Figure 3. Photo alignment settings in Agisoft Metashape.



Workspace (1 chunks, 187 images)
Chunk 1 (187 images, 214,836 tie points

Build Point Cloud
General
Source data: Depth maps
Quality: Ultra high
☑ Reuse depth maps
Advanced
Depth filtering: Aggressive
☑ Calculate point colors
☐ Calculate point confidence

faces: 141,295,338 vertices: 70,663,141

Figure 4. Sparse point cloud generation.

3. **Dense cloud generation:** From the achieved sparse cloud, a dense point cloud was generated, which enhances the detailing of the 3D model. This step facilitates the detection of subtle surface irregularities, such as potholes. Mesh and texture creation: A mesh is created from the dense point cloud, enhancing the physical surface. Then the mesh is applied with texture maps, which provide detailed visual information that helps to detect and distinguish potholes from textures and shadows, as shown in **Figure 5**.

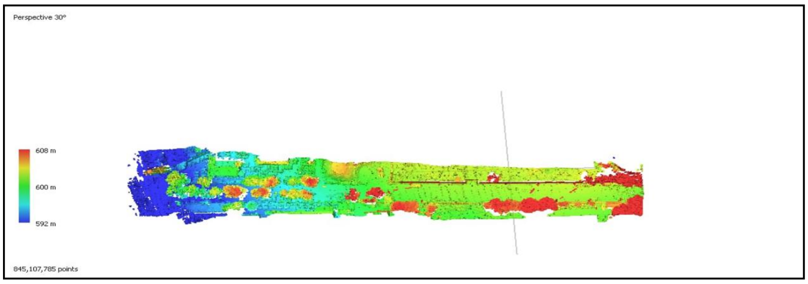
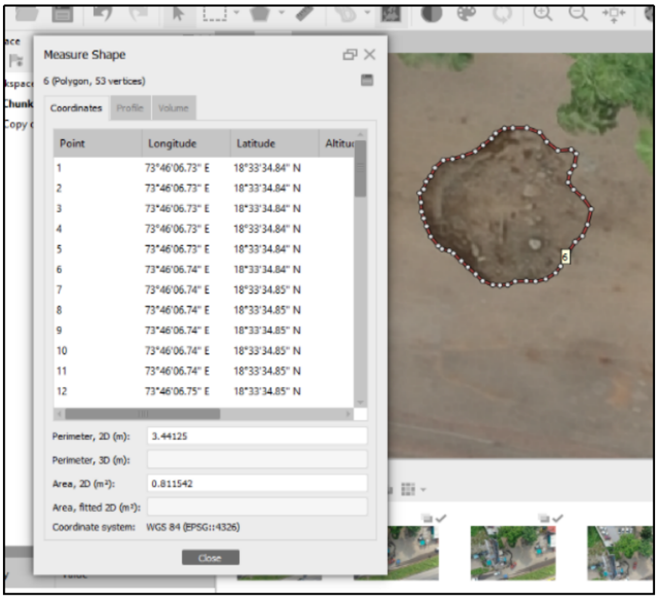


Figure 5. Color code for DEM.

4. **Orthomosaic generation and digital elevation model (DEM):** As shown in **Figure 6**, Digital Elevation Models (DEM) created from the 3D mesh capture vertical changes on road surfaces and highlight areas with depressions or raised surfaces. An orthomosaic image was created to obtain a scaled image for pothole mapping.

Figure 6. Lane1 Orthomosaic.

Area calculation in Agisoft Metashape: Method 1—As depicted in **Figures 7** and **8**, the first step is to choose the mesh model from the workspace, followed by selecting Tools > Measure Area & Volume. Next, the boundary of the pothole region is specified, and Metashape will automatically calculate the total surface area of the region, considering terrain changes. Method 2—This method uses QGIS to upload the Orthomosaic file. In the view tab > Measure, a polygon is drawn to measure the location of potholes.

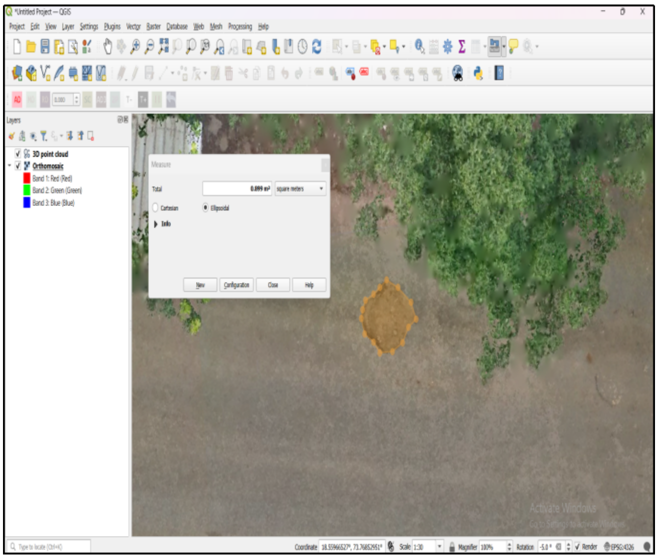


6 (Polygon, 53 vertices)

Point	Longitude	Latitude	Altitu
1	73°46'06.73" E	18°33'34.84" N	
2	73°46'06.73" E	18°33'34.84" N	
3	73°46'06.73" E	18°33'34.84" N	
4	73°46'06.73" E	18°33'34.84" N	
5	73°46'06.73" E	18°33'34.84" N	
6	73°46'06.74" E	18°33'34.84" N	
7	73°46'06.74" E	18°33'34.85" N	
8	73°46'06.74" E	18°33'34.85" N	
9	73°46'06.74" E	18°33'34.85" N	
10	73°46'06.74" E	18°33'34.85" N	
11	73°46'06.74" E	18°33'34.85" N	
12	73°46'06.75" E	18°33'34.85" N	

Perimeter, 2D (m): 3.44125
Perimeter, 3D (m):
Area, 2D (m²): 0.811542
Area, fitted 2D (m²):
Coordinate system: WGS 84 (EPSG::4326)

Figure 7. Agisoft Metashape.



Total 0.899 m² square meters
○ Cartesian ● Ellipsoidal

Figure 8. QGIS.

QGIS software details: The free and open-source Geographic Information System (GIS) software that supports a variety of geospatial data analysis is version 3.34.6 of QGIS. This software has advanced features that facilitate the processing of both vector and raster data. This makes it ideal for processes such as clipping orthomosaics, generating contours, and calculating volumes. This version also has user-friendly interfaces that facilitate plugin compatibility.

Steps for volume calculation in QGIS: The process of calculating pothole volumes using QGIS software. The pothole boundary was delineated using QGIS tools from the orthomosaic and DEM to generate contours and calculate volumes and areas below ground level. The version of QGIS software used for the task is QGIS (version 3.34.6)

1. **Clipping the orthomosaic:** The orthomosaic file was uploaded to QGIS using the tools (Layer > Add Layer > Add Raster Layer), and the pothole area was drawn manually using the polygon tool, as shown in **Figure 9**. Clipping was performed using the Raster > Extraction > Clip Raster by Mask Layer tool. The orthomosaic was selected as the input raster, and the pothole area polygon was chosen as the mask layer. The output of the clipped raster file of the given name (e.g., "Clipped Orthomosaic") was saved.

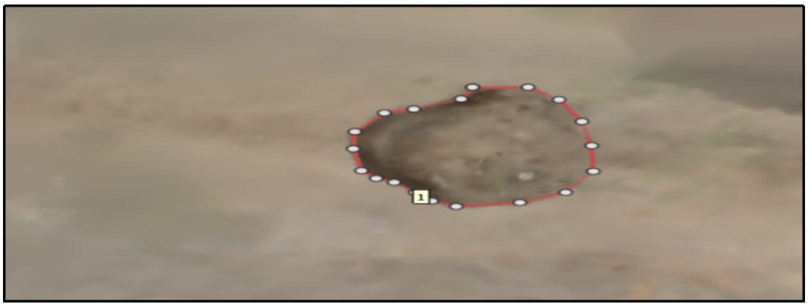
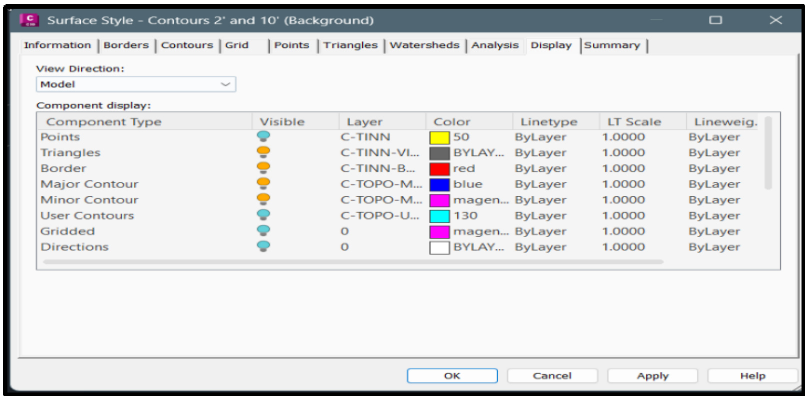


Figure 9. Marking a boundary in software.

2. **Generating contour lines:** A DEM file corresponding to the pothole area was loaded into QGIS, as shown in **Figure 10**. Raster > Extraction > Contour tool used for this step. The input data is DEM. Contour interval is set according to the requirements of the project. For example, the interval can be 1 m, 2 m, or 5 m. Contours are saved in a shapefile format, e.g., "Contours.shp". To make the output more comprehensible, elevation labels can be added to the contours. This can be done through the Layer Properties > Labels option. Contour lines are overlaid on the DEM/orthomosaic.
3. **Raster surface volume calculation**: As shown in **Figure 11**, the Raster Surface Volume tool is utilized for Volume calculation under the Raster > Analysis option. The clipped DEM was chosen as the input layer, and a base level was chosen, which is the reference level for the calculation. It creates a text report with the volume below the reference plane, along with a summary of the properties of the raster used for the calculation. The data was analyzed to identify significant patterns or anomalies.

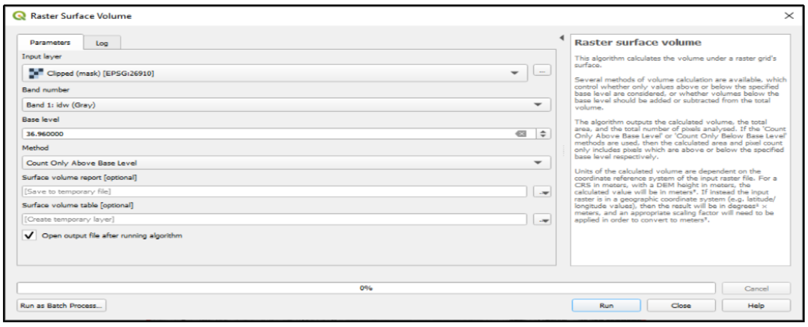


View Direction: Model

Component display:

Component Type	Visible	Layer	Color	Linetype	LT Scale	Lineweig.
Points	●	C-TINN	50	ByLayer	1.0000	ByLayer
Triangles	●	C-TINN-VI...	BYLAY...	ByLayer	1.0000	ByLayer
Border	●	C-TINN-B...	red	ByLayer	1.0000	ByLayer
Major Contour	●	C-TOPO-M...	blue	ByLayer	1.0000	ByLayer
Minor Contour	●	C-TOPO-M...	magen...	ByLayer	1.0000	ByLayer
User Contours	●	C-TOPO-U...	130	ByLayer	1.0000	ByLayer
Gridded	●	0	magen...	ByLayer	1.0000	ByLayer
Directions	●	0	BYLAY...	ByLayer	1.0000	ByLayer

Figure 10. Generating contour lines.



Input layer: Clipped (mask) [EPSG:26910]

Band number: Band 1: idw (Gray)

Base level: 36.960000

Method: Count Only Above Base Level

Surface volume report [optional]: [Save to temporary file]

Surface volume table [optional]: [Create temporary layer]

☑ Open output file after running algorithm

Raster surface volume

This algorithm calculates the volume under a raster grid's surface.

Several methods of volume calculation are available, which control whether only values above or below the specified base level are considered, or whether volumes below the base level should be added or subtracted from the total volume.

The algorithm outputs the calculated volume, the total area, and the total number of pixels analysed. If the 'Count Only Above Base Level' or 'Count Only Below Base Level' methods are used, then the calculated area and pixel count only includes pixels which are above or below the specified base level respectively.

Units of the calculated volume are dependent on the coordinate reference system of the input raster file. For a CRS in meters, with a DEM height in meters, the calculated value will be in meters^3. If instead the input raster is in a geographic coordinate system (e.g. latitude/longitude values), then the result will be in degrees^2 × meters, and an appropriate scaling factor will need to be applied in order to convert to meters^3.

Figure 11. Raster Surface Volume.

Step for manual pothole area and volume calculation: Used chalk or markers to mark the pothole boundaries. Place the grid on top of the pothole: Create a mesh pattern on top of the pothole using a ruler, measuring tape, or a prefabricated grill (for example, a 10 cm by 10 cm square grid. If the potholes are irregular, they fit into the grid size of the boundary line. Count the perfect lattice square: Count all lattice squares that fall entirely into the pothole limit. Calculate the total area: Multiply the total number of full squares and partial squares by the area of the grid square.

Table 1 compares the pothole area (m^2) and volume (m^3) obtained from software-based and manual measurement methods for 22 observations. The results indicate minimal deviation between the two methods, indicating strong agreement and confirming the reliability and accuracy of the software-based calculations. The accuracy of UAV-based measurements was statistically validated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and correlation coefficient (R^2).

Table 1. Comparison of pothole area and volume calculated using software-based and manual measurement methods.

	Software data		Manual data		Difference	
Sr. No.	**Area (m^2)**	**Volume (m^3)**	**Area (m^2)**	**Volume (m^3)**	**Area (m^2)**	**Volume (m^3)**
1	1.92332	2.3875	1.9123	2.3725	0.01102	0.015
2	0.811542	2.75271	0.8135	2.75424	−0.00196	−0.00153
3	0.28777	3.164289	0.2845	3.154289	0.00327	0.01
4	0.40179	2.98762	0.3954	2.985432	0.00639	0.002188
5	1.34774	3.7311	1.3456	3.73456	0.00214	−0.00346
6	0.4455	2.65717	0.4275	2.63465	0.018	0.02252
7	1.468	4.9986	1.4235	4.96653	0.0445	0.03207

Table 1. *Cont.*

	Software data		Manual data		Difference	
Sr. No.	**Area (m^2)**	**Volume (m^3)**	**Area (m^2)**	**Volume (m^3)**	**Area (m^2)**	**Volume (m^3)**
8	0.69533	1.31253	0.7002	1.31644	−0.00487	−0.00391
9	3.13406	3.94068	3.1367	3.94235	−0.00264	−0.00167
10	1.49081	1.061501	1.4756	1.04563	0.01521	0.015871
11	2.43011	2.76153	2.4136	2.742553	0.01651	0.018977
12	3.51517	2.96866	3.5356	2.96653	−0.02043	0.00213
13	2.57029	5.763535	2.5524	5.76462	0.01789	−0.001085
14	22.2956	6.154324	22.284	6.15234	0.0116	0.001984
15	4.39596	4.66594	4.4013	4.6734	−0.00534	−0.00746
16	0.68687	2.6774	0.683	2.67435	0.00387	0.00305
17	0.708468	1.1735	0.7046	1.1713	0.003868	0.0022
18	4.30115	7.45866	4.29	7.45783	0.01115	0.00083
19	0.33182	2.2882	0.3323	2.28634	−0.00048	0.00186
20	1.21075	4.827749	1.2072	4.825234	0.00355	0.002515
21	77.717	8.45687	77.72	8.46344	−0.003	−0.00657
22	55.541	5.8652	55.5327	5.86256	0.0083	0.00264
SUM	187.71005	84.055268	187.5715	83.94712	0.13855	0.10815

The results indicate: MAE (Area) ≈ 0.008 m^2; RMSE (Area) ≈ 0.012 m^2; $R^2 \approx 0.99$

Figure 12 illustrates the correlation between UAV-based and manual measurements of pothole area. The graph includes error bars representing measurement uncertainty. A strong linear relationship is observed, with $R^2 = 0.99$, indicating high agreement between the two methods. The inclusion of error bars further validates the robustness and reliability of UAV-based measurements.

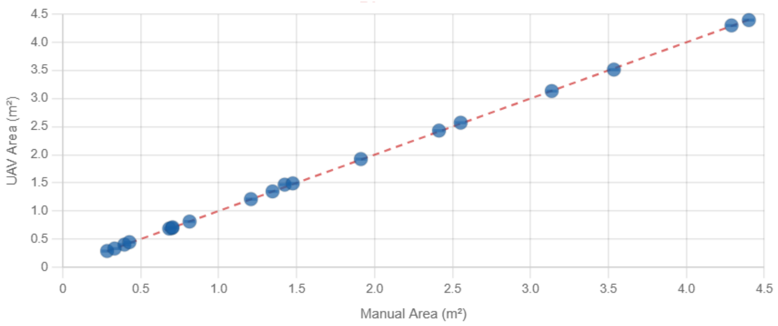


Figure 12. Correlation—UAV vs. Manual Area (m^2).

Table 2 shows that drone-based surveys have a higher initial daily cost (₹46,905) due to drone rental costs of approximately ₹40,000 per day and the use of licensed photogrammetry software like Agisoft Metashape and AutoCAD. But drone surveys reduce data processing time significantly (to approximately 2–6 h) due to automation and AI-enabled processing. This improves project efficiency and accelerates completion timelines. Also, logistics costs are low because deployment can happen from one place with fewer people. Although the initial daily cost of drone-based surveys is higher, the method significantly reduces project duration (by approximately 60–70%) and improves data accuracy. For large-scale road networks, this results in lower cost per kilometre and improved lifecycle cost efficiency. The time efficiency of UAV-based surveys was further quantified. On average, manual pothole measurement requires approximately 20–30 min per pothole, whereas UAV-based detection and processing reduce this to 8–10 min per pothole, resulting in a time saving of nearly

60–65%. For a 1 km road stretch containing approximately 40–50 potholes, this translates into a reduction of survey time from 20–25 h (manual) to approximately 8–10 h (UAV-based). Although the daily operational cost of UAV surveys is higher, the reduced project duration leads to a lower cost per kilometre in large-scale implementations. Over the lifecycle of road maintenance projects, this results in improved cost efficiency and resource optimization. A lifecycle perspective indicates that reduced inspection frequency, faster response time, and optimized material usage contribute to long-term savings, making UAV-based monitoring a sustainable alternative for infrastructure management.

Table 2. Comparative cost analysis of drone-based and traditional survey methods.

	Drone-based survey (estimated)	Traditional survey (estimated)	Reference
Drone Rental/Purchase Cost	₹40,000 per day	-	https://yelloskye.com/
Survey Equipment Cost	Included in drone rental (Lidar/RTK sensors if needed)	₹1,500 per day (Total station, GPS devices)	
Software Cost A. Agisoft Metashape	₹265 per Day (License)	-	https://www.agisoftmetashape.com/
B. QGIS, AutoCAD	₹390 per Day (License)	₹390 per Day (License)	https://www.autodesk.com/
Labour Cost (Per Day)	2 Drone operators: ₹4,000	5 Surveyors: ₹4,800	MH-SSR-23
Data Processing Time	2–6 h (Automated using AI tools)	1–3 days (Manual calculations, slower processing)	
Processing Engineer Cost	₹2,250 per day	₹5,500 per day	
Logistics & Transportation	Minimal (Drone deployment from a single point)	₹2,000 per day (Transporting surveyors & equipment)	
Total Estimated Cost Per Day	₹46,905	₹10,390	

Conventional method for pothole repairs (MORTH specification):

1. **Binder:** Two polymers used are modified bitumen (PMB 40) and Crumb rubber modified bitumen (CRMB 55). As per IS 15462 or IRC: SP:53, Binder content is 5.8% to 7.0% by weight of the mix;
2. **Aggregate gradation (gap graded):** (a) Normal maximum aggregate size is 13 mm–19 mm; (b) Coarse aggregate (Retained on 4.75 mm sieve): 70%–80%; (c) Fine aggregate (Passing 4.75 mm sieve but retained on 0.075 mm sieve): 8%–12%; (d) Filler (Passing 0.075 mm sieve): 8%–12% (Stone dust, Hydrated lime or Cement).
3. **Mixing and laying temperature:** Mixing temperature: 160 °C–170 °C, Laying temperature: 140 °C–160 °C

Table 3 shows the material specification and mix design parameters that were used for the pavement work, following the rules set out in IRC 27-2009. The total area to be treated is 187.71 m^2, and the volume of the treatment area is 84.055 m^3. The Marshall density of the mix is 2.31 t/m^3, and the bulk density of the aggregates is 1.6 g/cc, according to IS 2386 (Part 3)—1963.

Table 3. Material specification and mix proportion details (IRC 27-2009).

No.	Material specification	Parameters	Unit
1)	Total area	187.71	m^2
2)	Compacted Volume	84.055	m^3
3)	Marshall Density	2.31	t

Table 3. *Cont.*

No.	Material specification	Parameters	Unit
4)	Bulk Density of aggregates as per IS 2386 (Part 3)—1963	1.6	g/cc
5)	Coarse aggregate proportion	55%	
	37.5–25 mm	22%	Quantity of Aggregate
	25–10 mm	13%	Quantity of Aggregate
	10–4.75 mm	20%	Quantity of Aggregate
6)	Bitumen (Binder) Material	5%	
7)	Rice husk Material	35%	
8)	Filler (lime, cement, stone dust)	5%	
9)	Application Rate of Bitumen	0.75	kg/m^2

Table 4 shows a detailed cost comparison between the traditional way of paving and other eco-friendly materials, such as demolished material, coconut shell charcoal, HDPE plastic, and rice husk ash. The comparison is based on three main costs: the cost of materials, the cost of labour, and the cost of equipment. Then, the contractor's profit (10%), contingencies (5%), and overhead charges (8%) are added. The conventional method has the highest total material cost (₹872,712) because it uses more bitumen (VG-30/60-70 grade). Alternative materials show that bitumen and filler costs are lower, which means that overall material costs are lower. Rice husk ash has one of the lowest total material costs (₹751,560) of all the sustainable options. Coconut shell charcoal and HDPE plastic are close behind. The costs of labour and equipment become the same for all methods (₹10,200 each), which means that the main reason for the difference in costs is the materials used, not the construction process.

Table 4. Cost comparison of conventional and alternative mix materials.

Sr. No		Conventional method	Demolished material	Coconut shell charcoal material	HDPE plastic	Rice husk ash
(A)	**Material Cost**					
	Material Type	Total Cost (₹)	Total Cost (₹)	Total Cost (₹)	Total Cost (₹)	Total Cost (₹)
	Coarse Aggregate (Various Sizes)	230,572	230,580	230,580	230,580	230,580
	Fine Aggregate (Sand, Stone Dust, etc.)	64,560	48,420	64,560	64,560	64,560
	Filler (Stone Dust, Cement, Lime, etc.)	14,400	2,880	8,064	12,672	5,760
	Bitumen (VG-30, 60/70 Grade)	563,180	478,500	450,660	450,660	450,660
	Total Material Cost (₹)	872,712	760,380	753,864	758,472	751,560
(B)	**Labour Cost**					
	Labour Type	Total Cost (₹)	Total Cost (₹)	Total Cost (₹)	Total Cost (₹)	Total Cost (₹)
	Skilled Labour (Paver Operator, Supervisor)	6,000	6,000	6,000	6,000	6,000
	Unskilled Labour (Spreading, Compacting, Mixing)	4,200	4,200	4,200	4,200	4,200
	Total Labour Cost (₹)	10,200	10,200	10,200	10,200	10,200
(C)	**Equipment Cost**					
	Equipment Used	Total Cost (₹)	Total Cost (₹)	Total Cost (₹)	Total Cost (₹)	Total Cost (₹)
	Truck for Transportation	6,000	6,000	6,000	6,000	6,000
	Paver Machine	8,000	8,000	8,000	8,000	8,000
	Vibratory Roller	5,000	5,000	5,000	5,000	5,000
	Total Equipment Cost (₹)	10,200	10,200	10,200	10,200	10,200
	Total Cost	901,912	789,580	783,064	787,672	780,760
	Contractors Profit (10%)	90,191.2	78,958	78,306.4	78,767.2	78,076

Table 4. *Cont.*

Sr. No		Conventional method	Demolished material	Coconut shell charcoal material	HDPE plastic	Rice husk ash
	Contingencies (5%)	45,095.6	39,479	39,153.2	39,383.6	39,038
	Overhead Charges (8%)	72,152.96	63,166.4	62,645.12	63,013.76	62,460.8
	Total Cost	1,109,351.76	971,183.4	963,168.72	968,836.72	960,334.8

The total cost of the project using the traditional method is ₹1,109,351.76, which includes profit, contingencies, and overhead. Using different materials, on the other hand, results in significant cost reductions. The rice husk ash mix has the lowest total cost (₹960,334.8), and the coconut shell charcoal mix has the second lowest cost (₹963,168.72). This shows that they are economically more efficient.

The bar chart, as shown in **Figure 13**, shows the cost comparison among alternative materials and the conventional material. The total cost was relative to the traditional material, which defines the 100% baseline. The graph confirms that all alternative materials save costs, with Rice Husk saving the most at 13.43%, followed by Coconut Shell Charcoal at 13.18%.

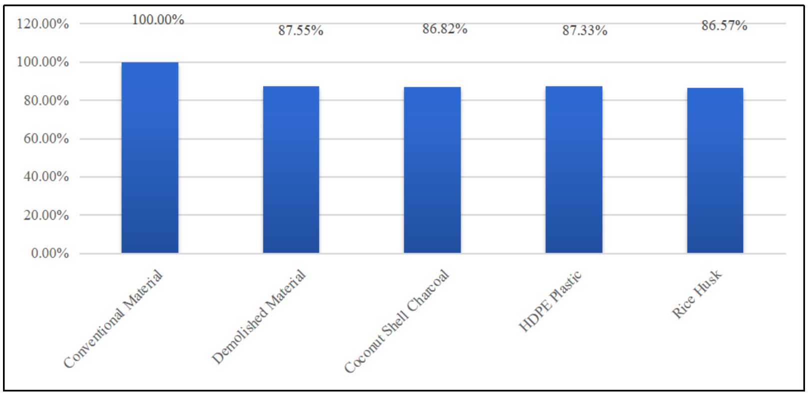


Figure 13. Comparison of material cost with the conventional method.

4. Conclusion

This study presents an integrated framework combining UAV-based pothole detection with sustainability-driven repair analysis, offering a scalable and cost-efficient solution for modern road maintenance systems. The findings highlight the advantages of drone-based inspection, including improved accuracy, reduced labour dependency, and faster data acquisition compared to traditional methods. It has also helped to understand the limitations of real-life implementation, the regulatory framework, and cost-benefit analysis, which are addressed in this study. Furthermore, the importance of using alternative filler materials such as coconut shell charcoal, HDPE plastic, rice husk ash, and demolished construction aggregates has been emphasized in previous studies. This methodology has used a structural approach to data collection, problem recognition, and experimentation.

These images were taken using drones that carry high-resolution cameras. Software like Agisoft Metashape and QGIS was used to quantify the potholes that were detected using the drone. The quantification of the potholes has an accuracy of 97–99% in comparison to the manual readings. The cost of drone surveying was 4.5 times more than the cost of manual surveying, but it can help in saving time and cost in the long run. The use of drones in pothole detection reduces human efforts while increasing the consistency of results. In the second phase of the study, a performance and cost analysis of the sustainable materials was done. The cost of using rice husk and coconut shell charcoal was reduced by 13.43% and 13.18%, respectively, in comparison to other conventional materials. These sustainable materials will not only help in cost reduction but will also contribute to environmental sustainability by reducing carbon footprints.

The findings of this study are consistent with previous research highlighting the advantages of UAV-based infrastructure monitoring. For example, Kuttah and Waldemarson reported that UAV-based road profiling significantly improves inspection efficiency compared with traditional methods. Similarly, Chen et al. demonstrated that modern pothole repair techniques can improve pavement durability. The results of this study extend these findings by integrating UAV-based detection with sustainable material analysis. While earlier studies focused either on detection technology or repair techniques, this research combines both aspects and demonstrates that drone-based detection can achieve measurement accuracy of approximately 97–99%, while sustainable materials such as rice husk ash and coconut shell charcoal can reduce repair costs by more than 13%. This integrated approach provides a more comprehensive framework for sustainable road maintenance. While the study demonstrates promising results, it is limited to a specific study area and a relatively small sample size. Future research should focus on validating the long-term durability and performance of sustainable materials such as rice husk ash and coconut shell charcoal under varying environmental and traffic conditions. Additionally, large-scale implementation of UAV-based monitoring systems should be explored to assess scalability across diverse infrastructure networks.

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