

Smart City Road Maintenance: A LiDAR and AI-Driven Approach for Detecting and Mapping Road Defects

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Giovanni Nardini

Giovanni Nardini holds a Master's degree in Mechanical Engineering from Sapienza University of Rome, and specialized in AI and Computer Vision. His current work involves combining insights from his engineering background with Artificial Intelligence and Computer Vision, focusing on developing solutions for real-world challenges. He now leads AI development at Key2, focusing on Computer Vision and Machine Learning applications.





The challenge of maintaining roads





Alternative technological approaches..



- limited detail on geometry
- depends on defect size
- depends on vehicle path
- Noise interpretation

location accuracy is poor

suffers from lightning conditions

• detections are in 2D, very poor size estimation

Our Approach



Position (



IMU/GNSS



Outputs: Detection of both pothole and cracks

defects

• Scene understanding / relative positions

 3D reconstruction of detected items

Estimation of Extension / Depth and Volume of detected items

 Accurate in-road positioning of each detected item

Hardware Setup



A vehicle-mounted system designed for continuous and automated road monitoring



Software Architecture



Framework: Robot Operating System (ROS)

• Input Sensors drivers Nodes (Lidar,

USB_Camera, GNSS/INS) → publish

Synchronization algorithm

- < subscribe, Al Node, gets RGB image and applies models:
 - Road defects instance segmentation
 - Scene semantic segmantation
 - \circ Garbage detection \rightarrow publish
- < subscribe, **3D processing Node**, applies:
 - Camera Lidar fusion
 - Point Cloud detection projection
 - Detected items reconstruction and
 - measurement → publish
- < subscribe, Geolocation and data sending
 - **Node** → Cloud

Multi-sensor Synchronization

Challenge: LiDAR, Camera, and GNSS/INS sensors operate at different frequencies and generate data asynchronously.

Why it's Crucial: Precise temporal alignment (synchronization) is essential for:

- Accurately projecting 2D detections (from Camera) onto the corresponding 3D point cloud (from LiDAR).
- Associating the correct vehicle pose (from GNSS/INS) with each sensor measurement.
- Ensuring reliable geolocation of detected road defects.



Al models applied to RGB frames



Output:

- Masks and Bounding Boxes of each detected pothole (red)
- Mask of all cracks (yellow)



YOLO-Nano Garbage Detection Architecture



Output:

Bounding Boxes of each detected garbage instance (blue)

SegFormerB1 Scene Semantic Segmentation Architecture



Output:

Mask of semantic segmentation (each pixel is classified into specific classes)

3D Lidar-Camera Fusion

PointCloud

EIGHT 1080

RGB MAGE

Goal: To combine the strengths of both sensors, leveraging the AI's ability to detect defects in rich 2D camera images and the LiDAR's ability to provide precise 3D geometric measurements.

Requires:

- Extrinsic Parameters: The precise 3D position and orientation of the camera relative to the LiDAR sensor.
- $\begin{bmatrix} R \mid t \end{bmatrix} = \begin{bmatrix} r_{1,1} & r_{1,2} & r_{1,3} & t_1 \\ r_{2,1} & r_{2,2} & r_{2,3} & t_2 \\ r_{3,1} & r_{3,2} & r_{3,3} & t_3 \end{bmatrix} \quad CamWorld(x,y,z) = \mathbf{RT}^*LidarWorld(x,y,z)$ • Intrinsic Parameters: Camera's internal characteristics (focal length, principal point, distortion).

$$K = \begin{pmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{pmatrix} \qquad Image(u,v) = K*CamWorld(x,y,z)$$

$$Depthmap$$

Lidar Depthmap on Image To Point Cloud MAP LIDAR FUSION WIDTH 1930 MASKS CHANNELS POINT CLOUD MAP

3D Measurements



Once defects are projected onto Point Cloud

- Pothole volume (how much asphalt) [cm3]

Convex Hull Algorithm

Crack mask and scene semantic segmentation are used together to compute cracks percentage over total asphalt:

Results: Defects segmentation AI performance

Validation Context: The AI model was rigorously evaluated on dedicated test datasets, reflecting diverse urban road conditions.

Performance metrics:

 Mean Average Precision (mAP @ IoU 0.5:0.95): 0.56
 Interpretation: Reflects robust performance in detecting and segmenting potholes and alligator cracks across various sizes and appearances.

$$mAP = rac{1}{k}\sum_{i}^{k}AP_{i}$$

• F1-Score: 0.57

Interpretation: Indicates a solid balance between Precision (minimizing false detections) and Recall (capturing most actual defects).

Precision =
$$\frac{TP}{TP + FP}$$
 TP = True positive $Recall = \frac{TP}{TP + FN}$ FP = False positive FN = False negative FN = False negative

 $F1 = 2 \cdot \frac{precision \cdot recall}{precision + recall}$



Results: Road segmentation Al performance

Validation Context: The AI model was rigorously evaluated on dedicated test datasets, reflecting diverse urban road conditions.

Performance metrics:

• Mean Intersection over Union (mIoU): 0.43 Interpretation: Shows the model's capability to accurately outline the general road area within the scene.

Area of Union



• F1-Score (for 'Road' class): 0.98

Interpretation: Highlights exceptional reliability and precision in identifying the road surface itself, crucial for filtering out non-road detections.









Results: 3D measurements performance

Validation Context: the performance of depth, extension and volume estimation has been evaluated by manual measuring (laser distance meter, on-site) a selection of real potholes.

3D Defect Dimensions:

Enabled by projecting AI detections onto the LiDAR point cloud for reconstruction

- **Depth:** relative error percentage of **24%**
- **Extension:** relative error percentage of **6%**
- Volume: relative error percentage of 19%

Interpretation: Demonstrates quite high accuracy in quantifying the actual physical size of detected potholes. The extension is the most reliable measurement.





• LiDAR intrinsic error: +5cm/-5cm at long range

• Sparse Point Cloud:

points decrease density at longer range

Motion effects

Results: Web app navigation





Heatmap of cracks:

which segments are the most affected



Processed roads:

shows the areas that has been scanned with the system







Information Box for each

detection:

- STATUS
- IMAGE
- EXTENSION
- DEPTH
- VOLUME
- COORDINATES
- DETECTION TIMESTAMP

Images of each detection (red mask-> pothole, yellow mask-> crack)

3D Scene point cloud with colorcoding

Conclusions & Future Works



Future works:

- Sparse to Dense
 Depth Completion
- Exploring

 alternative
 approaches to
 LiDAR (mono and
 stereo depth
 estimation from
 Images)



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Q&A Thanks

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