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Mobile Pothole Detection and Reporting Using YOLOv8 for Smart Municipal Governance

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Abstract - *Pothole reporting systems require reliable detection and a municipal workflow that citizens can understand and trust. This study examines public requirements for a mobile-accessible Pothole Management System combining YOLOv8 image analysis, geolocation, and repair-status tracking. A cross-sectional Google Forms survey produced 82 submissions between 19 September and 6 October 2026. Frequencies, multiple-response analysis, data-quality checks, and an exploratory two-sided Fisher's exact test were applied. A focused review compared 12 relevant studies, including nine published during 2024–2026. Among all submissions, 96.3% reported encountering potholes at least weekly, 75.6% indicated never reporting one, and 86.6% expressed willingness to use the proposed system. Status updates, repair photographs, and estimated completion dates were the most frequently selected features. After retaining the earliest submission per email and excluding one missing reporting-history answer, willingness differed between never reporters and previous reporters (93.5% versus 72.2%; n = 80; p = 0.0239). This association is exploratory and does not establish causation. Separately, the existing project manuscript reports 40 passed cases out of 53 functional tests; these results do not measure detection accuracy. The findings support user-controlled reporting and traceable repair coordination, while model performance, field effectiveness, and population-level adoption remain unvalidated.*

Keywords - Pothole detection; YOLOv8; mobile crowdsensing; municipal governance; geolocation; citizen reporting.

1. INTRODUCTION

Potholes affect journey comfort, vehicle condition, and road safety. Smartphone cameras and sensors provide accessible ways to collect road-condition evidence, while machine learning can assist its interpretation. Earlier work established smartphone image datasets [1], sensor-based classification [2], and collaborative cloud mapping [3]. These capabilities can support municipal reporting, but a detected defect still requires verification, assignment, repair, and confirmation.

The Pothole Management System (PMS) described in the existing project manuscript accepts citizen photographs and geolocation through a React interface, processes images with YOLOv8, and coordinates administrators and contractors.

This study adds survey evidence to identify reporting barriers, willingness to use the system, location-sharing preferences, and repair-tracking priorities. Its contribution is an empirical requirements assessment for this workflow, rather than a new detection algorithm.

2. PROBLEM STATEMENT

The technical problem is to connect mobile capture of a possible pothole with reliable image verification and an auditable municipal repair workflow while respecting user preferences. This study investigates which reporting and tracking requirements the sampled users prioritize and whether previous reporting experience is associated with willingness to use the proposed system. It does not assume that automated detection alone produces faster repairs.

3. LITERATURE REVIEW

A focused review used publisher pages, journal articles, and author manuscripts available through 18 October 2026. Searches covered smartphone pothole detection, YOLO, road-damage datasets, sensor fusion, and municipal management. Twelve relevant publications were selected, with emphasis on 2024–2026 (nine studies). This is a targeted comparison, not an exhaustive systematic review. Table I separates input data, reported performance, and remaining scope. Metrics from different datasets, devices, classes, and test protocols cannot be ranked as equivalent measurements.

Recent studies establish meaningful advances in mobile inference [8], depth measurement [9], [11], lightweight detection [10], and municipal risk prioritization [12]. The present survey addresses a complementary question: which reporting controls and accountability features users in this sample would value. A detection score, a depth-error metric, and a survey percentage describe different outcomes.

TABLE I. COMPARISON OF RELEVANT RESEARCH

Study	Method and dataset	Reported findings and metrics	Limitations or scope for this study
Maeda et al. [1] 2018	CNN-based detection; 9,053 smartphone images and 15,435 road damage instances from Japan.	Eight damage categories; evaluation includes accuracy and runtime on a phone and GPU.	Foundational benchmark; Japan-specific data and a combined damage class limit pothole-only interpretation.
Wu et al. [2] 2020	Logistic regression, SVM and random forest on smartphone vibration features collected in road trials.	Random forest: 88.5% precision and 75.0% recall.	Vehicle, placement and operating conditions affect transfer; detection evidence does not establish repair outcomes.
Ramesh et al. [3] 2022	Motion and vision models with smartphone data; cloud fusion merges vehicle detections into a road-condition map.	Evaluates classification and collaborative spatial merging; no single comparable pothole metric used here.	Demonstrates prior integration; citizen acceptance and verified repair closure require separate evaluation.
Arya et al. [4] 2024	RDD2022: 47,420 images, over 55,000 damage instances and four classes across six countries.	Reported challenge-best F1: 76.9% across road-damage categories.	Broad benchmark, not a pothole-only score or evidence of municipal response effectiveness.
Kim and Kim [5] 2024	RDD-CNN uses 1,137 automatically labelled sensor samples with dashcam assisted collection.	Pothole classification accuracy 86.77%; approximately 0.1 s processing per minute of driving.	Classifies bumps, manholes and potholes; performance depends on phone placement.
Safyari et al. [6] 2024	Review of 2D vision, 3D point clouds and machine/deep learning across published datasets.	Compares accuracy, runtime, reliability and sensor cost; no new common benchmark score.	Heterogeneous evaluations hinder direct comparison; environmental robustness remains important.
Khandakar et al. [7] 2025	Multi sensor road-safety dataset includes accelerometer, gyroscope, GPS, gravity and orientation measurements.	Sensor-signal validation supports road anomaly research; no new municipal adoption result.	Useful for future sensing experiments; detection classifiers and local field transfer need validation.
Amri and Kusuma [8] 2025	YOLOv8 small/nano, YOLOv7 tiny and Faster R-CNN; 4,180 split images; Redmi Note 12 trials.	AP: 83.5% (small), 82.5% (nano); nano inference: 0.72 s/image.	Device-specific speed and accuracy trade-off; small or distant potholes and lighting remain challenges.
Zhong et al. [9] 2025	YOLOv8 with depth-camera point cloud fusion; experiments along a 4.7 km road section.	Precision 95.8%, recall 93.3%, F1 94.53%; 0.23 s/image on well-maintained surfaces.	Geometry helps filter false positives; depth-camera requirements exceed ordinary RGB-phone capture.
Li et al. [10] 2026	ECC-YOLO modifies YOLOv11n using deformable convolution, contrast aggregation and attention; pothole image dataset.	Recall 67.9%; mAP@0.5 74.2%, versus 72.8% for the baseline.	Domain transfer, reflective/water-filled potholes and deployment optimization remain open.
Rauf Butt et al. [11] 2026	MiDaS-DPT and refinement; 25,000 RGB–LiDAR pairs from an iPhone 14 Pro in Lahore.	Evaluates MAE, RMSE, inverse RMSE and depth-threshold accuracy; reports improved depth estimation.	Phone-specific training data, scale calibration and transformer cost constrain broad deployment.
Noh et al. [12] 2026	Six predictive models, SHAP and DBSCAN; 21,397 spatial points from Gwangju, 2022–2024.	Random forest: 90.47% accuracy, ROCAUC 0.957; 14 management hotspots.	Supports risk prioritization; local data and untested clustering sensitivity constrain transfer.

4. RESEARCH GAP

The reviewed literature already includes smartphone detection, cloud mapping and municipal decision support. Therefore, the gap is not the absence of integrated pothole systems. The narrower gap addressed here is the limited local evidence connecting citizens' reporting experience and adoption intentions with explicit design requirements for location consent, report progress, and repair verification. The study contributes descriptive evidence and an exploratory association test for these requirements; it does not claim algorithmic novelty or global uniqueness.

5. RESEARCH QUESTIONS

RQ1: What pothole exposure, impacts and reporting barriers are recorded in the survey?

RQ2: Which reporting modes, location-sharing conditions and municipal tracking features are preferred, and is willingness associated with previous reporting experience?

RQ3: Which improvements to the documented PMS workflow follow from these preferences and the existing functional-test evidence?

6. RESEARCH OBJECTIVES

O1: Quantify pothole exposure, reported impacts and reporting barriers using frequencies and explicitly stated denominators.

O2: Measure system preferences and test the association between reporting history and willingness using a two-sided Fisher's exact test at $\alpha = 0.05$.

O3: Translate the highest-ranked needs and documented test failures into specific system and municipal-workflow recommendations.

7. HYPOTHESIS

H_0: Previous pothole-reporting experience and positive willingness to use the proposed system are independent (odds ratio = 1).

H_1: Previous pothole-reporting experience and positive willingness are associated (odds ratio ≠ 1).

Positive willingness combines "Very likely" and "Somewhat likely"; the other observed category is "Somewhat unlikely." Reporting history is grouped as never reported versus any stated reporting channel. The grouping follows the meaning of the answers. The hypothesis is exploratory because it was not registered before examining the survey.

8. RESEARCH METHODOLOGY

8.1 Research Design and Sample

The study uses a cross-sectional descriptive survey with an exploratory association analysis and a documentary review of the existing system. The Google Forms export [13] supplied 82 submissions dated 19 September–6 October 2026. The questionnaire covered personal/travel characteristics, pothole experiences, reporting history, system preferences, and municipal-response requirements. No survey weights are applied. The actual exported answer categories, rather than unused options from the draft questionnaire, determine the analysis.

8.2 Data Preparation and Denominators

All 82 submissions are retained for descriptive tables to preserve the received dataset. Names and email addresses are omitted from results. Emails are normalized by trimming whitespace and lowercasing solely to identify repetitions. One email appears twice; retaining its earliest timestamp yields 81 distinct-email records. One of these lacks reporting history, leaving 80 complete records for the primary hypothesis test. This operational rule does not prove participant identity.

There are no identical complete rows. Reporting channel has one missing answer, reporting outcome three, and reporting deterrent two. Five never-reporters nevertheless provide an outcome, and one channel-reporting submission selects "never reported" as its outcome. Outcome analysis is restricted to the 18 raw submissions that identify a channel and an applicable outcome. No missing values are imputed.

Pothole impacts, reporting modes and feature priorities are processed as multiple-response items using exact option text. This avoids splitting options at internal commas. Twenty-three submissions select multiple reporting modes. Ten select four or five features despite the three-feature instruction; a sensitivity table excludes these answers only for that item. Percentages use the stated eligible denominator and are rounded to one decimal place.

8.3 Analysis Procedure

Frequencies and percentages summarize categorical answers. Open-ended comments are read for recurring suggestions; punctuation-only, blank and unclear entries are not treated as substantive suggestions. No quantified thematic prevalence or inter-rater reliability is claimed. A 2 × 2 cross-tabulation evaluates reporting history and willingness. Fisher's exact test is preferred to a chi-square approximation because an expected cell count is 2.025, below five. The analysis reports the two-sided p-value, sample odds ratio and conditional exact confidence interval.

Sensitivity checks retain the later repeated-email submission instead, and also analyze all complete raw submissions. They assess dependence on the duplicate-handling choice, rather than supply additional hypotheses. Results assume the remaining records represent independent observations; common recruitment networks and unidentified repeat submissions may weaken that assumption. Statistical significance does not establish population representativeness or causation.

8.4 Tools and Technologies

Google Forms and its Excel export provide the survey data. Python with openpyxl reads the workbook; standard counting routines compute frequencies; SciPy 1.17.0 performs Fisher's exact test and conditional odds-ratio intervals; Matplotlib 3.10.8 produces the charts. Microsoft Word format is used for manuscript presentation. These analysis tools are distinct from the application stack.

The documented PMS stack consists of React.js, Node.js/Express, MongoDB, a Python-based YOLOv8 inference service, and Nodemailer notifications. The revision does not execute or retrain YOLOv8. Model weights, training splits, confidence thresholds, image-level ground truth and device benchmarks were not supplied; no new detection performance values are asserted.

8.5 System Workflow and Evaluation Scope

The documented workflow is citizen image and location submission, image analysis, storage, administrator verification and contractor assignment, followed by status updates. Survey-informed additions are explicit location controls, acknowledgement IDs, estimated repair dates, photographic closure evidence, and a route to reopen unresolved reports. These additions are recommendations until implemented and tested. Continuous smartphone-sensor detection is future work; the documented web application requires image submission.

The prior manuscript [14] records 53 functional cases across user, administrator and contractor modules. Those totals are retained as a separate evidence stream and attributed to the existing project records. No new execution logs or repair outcomes are available. Access-control and workflow failures are treated as substantive defects, not dismissed as harmless edge cases.

9. DATA ANALYSIS AND INTERPRETATION

9.1 Respondent Profile and Exposure

TABLE II. PROFILE AND POTHOLE EXPOSURE (N = 82)

Variable and category	n	%
Age: under 18	8	9.8
Age: 18–24	62	75.6
Age: 25–34	5	6.1
Age: 35 or above	7	8.5
Travel: train or metro	34	41.5
Travel: two-wheeler	21	25.6
Travel: auto	17	20.7
Travel: four-wheeler	10	12.2
Potholes: daily	46	56.1
Potholes: a few times/week	21	25.6
Potholes: about once/week	12	14.6
Potholes: never	3	3.7

The sample is young and includes substantial public-transport use. Train/metro users may encounter potholes during connecting travel, but that exposure is not separately measured. Seventy-nine submissions (96.3%) report encounters at least weekly. Location entries contain overlapping city and locality names, so no unverified citylevel grouping is used.

TABLE III. SELF-REPORTED IMPACTS (N = 82)

Impact in past six months	n	%
Travel discomfort	66	80.5
Travel delays	37	45.1
Vehicle damage	30	36.6
Accident or injury	15	18.3

Multiple impacts could be selected. These answers establish perceived burden within the sample, not verified injury incidence or monetary loss. Discomfort is the most frequently recorded impact.

9.2 Reporting Behaviour and Barriers

Sixty-two submissions (75.6%) indicate never reporting a pothole. Nineteen (23.2%) identify a channel: seven in-person complaints, six municipal websites/apps and six

email/written complaints. One response is missing. Among the 18 submissions with a channel and an applicable outcome, nine (50.0%) report no acknowledgement and no repair, six (33.3%) do not know the outcome, and three (16.7%) report a full repair. This small, selected subgroup cannot estimate municipal repair performance.

TABLE IV. MAIN REPORTING DETERRENT (VALID N = 80)

Deterrent	n	%
Concern no action will follow	37	46.3
Not knowing where/how to report	29	36.3
Time or effort required	8	10.0
Difficulty specifying location	6	7.5

The two largest barriers concern expected response and knowledge of the reporting channel. This supports combining a simple submission flow with visible acknowledgement and progress tracking. Two missing answers are excluded from this denominator.

9.3 Willingness and Reporting Preferences

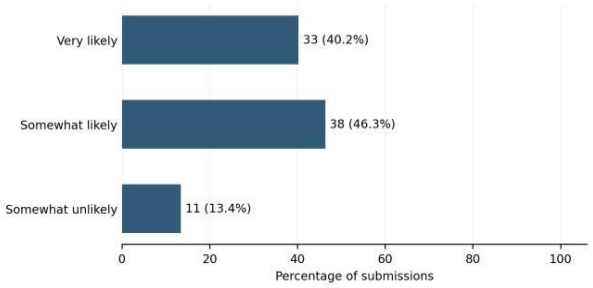


Fig. 1. Willingness to use the proposed system (82 submissions).

Positive willingness totals 71/82 (86.6%). After earliest-email deduplication it is 71/81 (87.7%). Neither percentage demonstrates actual adoption. The survey describes a hypothetical system rather than providing a usability trial.

TABLE V. REPORTING OPTIONS SELECTED (N = 82)

Option	n	%
Manual photo submission	50	61.0
Automatic detection with review	37	45.1
Automatic submission on chosen trips	29	35.4
Would use none	1	1.2

Because 23 submissions select multiple options, Table V reports support for each mode rather than exclusive first preferences. Manual reporting has the broadest recorded support, while automatic detection with review also attracts interest. A staged design can offer both.

9.4 Location Sharing and Concerns

TABLE VI. LOCATION-SHARING CONDITIONS (N = 82)

Condition	n	%
Individual report only	44	53.7
Condition	**n**	**%**
Background detection enabled	20	24.4
Explicitly chosen trips	11	13.4
Would not share location	7	8.5

Fifty-five submissions (67.1%) select report-specific or explicitly chosen-trip sharing. This supports controls that make the active collection period visible. Seven (8.5%) would not share location, creating a participation constraint for precise geotagging.

The biggest concerns are lack of municipal action (38/82; 46.3%), incorrect detections (24; 29.3%), data use or unreliable internet (11; 13.4%), and application difficulty (9; 11.0%). These are the observed answers; an absent response category does not establish that the corresponding issue is unimportant.

9.5 Municipal Features and Suggestions

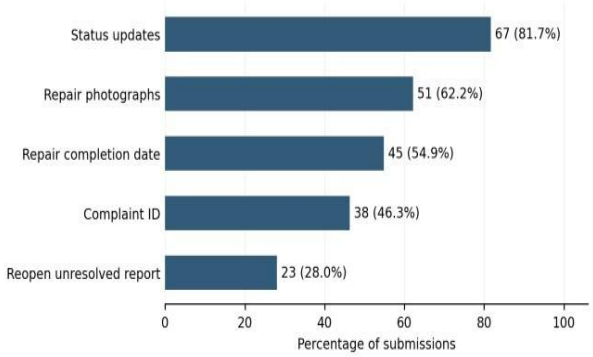


Fig. 2. Selected municipal features (multiple answers; N = 82).

TABLE VII. FEATURE-LIMIT SENSITIVITY

Feature	All 82 n (%)	Within limit 72 n (%)
Status updates	67 (81.7)	57 (79.2)
Repair photographs	51 (62.2)	41 (56.9)
Estimated comple-tion	45 (54.9)	36 (50.0)
Complaint ID	38 (46.3)	28 (38.9)
Reopen unresolved report	23 (28.0)	17 (23.6)

Excluding ten answers that exceed the three-feature limit preserves the full ranking. Status updates, repair photographs and estimated completion dates remain the top three. Open ended responses also request faster action, clear timelines, accountable follow-up, easy image/location reporting, and durable repairs. These observations are qualitative summaries, not independently coded theme frequencies.

9.6 Hypothesis Testing

TABLE VIII. REPORTING HISTORY AND WILLINGNESS

History	Positive	Somewhat unlikely	Total
Never reported	58	4	62
Previously re-ported	13	5	18
Total	71	9	80

The primary table retains the earliest response per normalized email and excludes the one missing reporting-history answer. Positive willingness is 58/62 (93.5%) among never-reporters and 13/18 (72.2%) among previous reporters, a descriptive difference of 21.3 percentage points.

The two-sided Fisher's exact test gives p = 0.0239. At α =

0.05, H_0 is rejected for this exploratory analysis. The sample odds ratio is (58 × 5)/(4 × 13) = 5.58 for never-reporters relative to previous reporters. The conditional odds-ratio estimate is 5.42, with a 95% exact confidence interval of 1.01– 31.42. The wide interval indicates substantial uncertainty.

Retaining the later repeated-email submission gives p = 0.0071 (n = 80); including both submissions gives p = 0.0092 (n = 81 complete answers). The direction and 0.05 decision are unchanged. The result suggests an association in the available records, but cannot show that previous reporting causes lower willingness. Age, recruitment and prior service experiences may confound the relationship.

9.7 Existing Functional-Test Evidence

TABLE IX. DOCUMENTED PMS FUNCTIONAL TESTS

Module	Tests	Pass	Fail	Pass %
User	20	18	2	90.0
Admin	14	10	4	71.4
Contractor	19	12	7	63.2
Total	53	40	13	75.5

Table IX reproduces the aggregate results in the existing PMS manuscript, not tests run during this survey analysis. The 75.5% pass rate is unrelated to YOLOv8 detection accuracy. The documented failure examples include unauthenticated admin access, assignment of unregistered contractors, closure without inspection, missing location permission and oversized uploads. The source lists only five scenario categories for thirteen failures, so detailed test traceability remains incomplete.

10. MAJOR FINDINGS

First, frequent exposure coexists with low reporting: 79/82 submissions encounter potholes at least weekly, whereas 62/82 have never reported one. Second, willingness to use the proposed system is high in the sample (71/82), with an exploratory association between reporting history and willingness after deduplication. Third, municipal response is central: inaction leads both the deterrent and concern responses, and status updates, repair photographs and estimated completion dates lead feature preferences. Fourth, reporting and location controls should remain flexible. Finally, the existing functional-test record identifies defects that require correction before a field pilot.

11. RECOMMENDATIONS

1. Municipal authorities should provide a complaint ID, named responsibility, visible status transitions and an estimated completion date that can be re-vised with a reason.
2. Closure should require repair evidence and allow citizens to flag unresolved damage.
3. A pilot should track time to acknowledgement, as-signment and verified closure, plus reopened-report rates, rather than use submission counts alone as success indicators.
4. Developers should prioritize the three leading tracking features, retain manual photo reporting,

and offer optional automatic detection with user review.
5. Location capture should be limited to an explicitly selected report or trip by default.
6. Offline queuing and simple interfaces address recorded connectivity and usability concerns.
7. Photos should be screened for unrelated personal content before wider access.
8. Before deployment, enforce server-side authorization, registered-contractor checks, upload validation and valid inspection-to-closure transitions.
9. Evaluate detection with held-out local images, reporting precision, recall, mAP, false-positive examples and phone-specific latency.
10. Image detections should assist municipal verification; they should not be treated as validated depth or severity measurements without calibration.

12. LIMITATIONS OF RESEARCH

1. Sample and data limitations: The dataset contains 82 submissions and 81 distinct email addresses, with no documented probability sampling frame or invitation denominator, and is treated as a non-probability voluntary-response sample. Most submissions are from the 18–24 age group (75.6%) and locations are concentrated around Mumbai and nearby areas, so findings cannot represent all citizens or municipalities. Responses measure self-reported experiences and hypothetical willingness, not observed adoption or verified road outcomes. Eight submissions indicate an age below 18, and ethics approval and any guardian consent arrangements are not documented. The hypothesis was formulated during secondary analysis, making the test exploratory.
2. Technical and evaluation limitations: No new image dataset, detector training, precision/recall benchmark, mobile latency test, or municipal pilot was conducted. Existing functional-test totals are documentary evidence, not a fresh independent replication. Battery, location accuracy, weather robustness, and actual repair-time improvements remain unmeasured.

13. CONCLUSION

The study addresses RQ1/O1 by quantifying exposure, impacts and barriers; RQ2/O2 by measuring preferences and testing the reporting-history association; and RQ3/O3 by mapping these results and documented test failures to workflow improvements. The survey supports a mobile accessible PMS that combines YOLOv8-assisted image screening with controlled location sharing and traceable repair coordination. The exploratory association is statistically significant under the stated model but remains sensitive to sampling and measurement limitations. The evidence supports requirements prioritization, while detection accuracy, sustained adoption and municipal service improvements require independent evaluation.

14. FUTURE SCOPE OF RESEARCH

Future work should recruit a larger sample across age groups, travel modes and municipal wards using a documented sampling strategy, with an adult-only or appropriately approved minor-participation protocol. A preregistered follow-up can validate the reporting-history association and measure changes after actual system use. Technical extensions should compare YOLO variants on geographically separated local test sets, measure battery/data costs, and evaluate accelerometer–camera fusion. Depthaware approaches may support calibrated severity estimation where suitable hardware is available. Federated learning, privacy-preserving image handling and duplicate-report clustering warrant evaluation. A municipal pilot should compare repair timelines and independently verified closure before and after deployment, accounting for staffing, budgets and seasonal road conditions.

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