

FixMyPath: Smartphone Sensor-Based Pothole Detection Using Machine Learning

Mohammad Imran Khan
Department of Computer Science and
Engineering

Jhulelal Institute of Technology
Nagpur, India
m.imran@jitnagpur.edu.in

Nisha Khubchand Khubnani
Department of Computer Science and
Engineering

Jhulelal Institute of Technology
Nagpur, India
ugf23cs038@jitnagpur.edu.in

Anisha Nagesh Gaikwad
Department of Computer Science and
Engineering

Jhulelal Institute of Technology
Nagpur, India
ugf23cs004@jitnagpur.edu.in

Aditya Liladhar Vaidya
Department of Computer Science and
Engineering

Jhulelal Institute of Technology
Nagpur, India
ugf23cs079@jitnagpur.edu.in

Harshpreet Kaur Ranjeet Singh
Ramgadiya
Department of Computer Science and
Engineering

Jhulelal Institute of Technology
Nagpur, India
ugf23cs019@jitnagpur.edu.in

Owesh Akram Khan
Department of Computer Science and
Engineering

Jhulelal Institute of Technology
Nagpur, India
ugf23cs117@jitnagpur.edu.in

Abstract—Road potholes remain a persistent hazard contributing to vehicular damage, traffic fatalities, and infrastructure degradation, particularly in developing nations. Conventional road-inspection workflows depend on manual surveys by municipal agencies, an approach that is labour-intensive, slow, and financially prohibitive at scale. This paper introduces FixMyPath, a low-cost, end-to-end pothole-detection framework that harnesses the built-in accelerometer of a commodity Android smartphone together with a Random Forest classifier. During a data-collection phase, vibration readings along three orthogonal axes were gathered at 50 Hz from a vehicle traversing real road segments in Nagpur, India. A resultant-magnitude feature was derived to decouple detection performance from handset orientation. The trained classifier discriminates among three road-surface classes—smooth road, speed breaker, and pothole—achieving an overall accuracy of 94.3 % on a held-out test partition. A companion Android application performs inference in near real-time (mean latency ≈ 18 ms per window) and notifies the rider through visual and auditory alerts upon pothole detection, while logging timestamped events for retrospective analysis. The proposed system offers a scalable, crowdsourcing-ready alternative to purpose-built road-survey vehicles and paves the way for city-wide road-quality mapping.

Keywords—Pothole detection; smartphone accelerometer; Random Forest; road anomaly classification; smart transportation; Android application; crowdsourced road monitoring.

I. INTRODUCTION

Road surface quality is a foundational pillar of urban mobility, directly influencing transportation safety, vehicle longevity, and the economic productivity of cities. Potholes—depressions formed by the cyclical freezing and thawing of subgrade moisture, heavy-vehicle loading, and deferred maintenance—rank among the most prevalent road defects worldwide. In India alone, the Ministry of Road Transport and Highways reports thousands of road-accident fatalities attributable to poor road conditions every year. Beyond the human cost, potholes inflict billions of rupees in

annual vehicle-repair expenditure and impose delays that erode freight efficiency.

Traditional road-inspection practice is grounded in periodic visual surveys conducted by trained technicians. While this approach provides reliable ground truth, it suffers from well-documented limitations: high manpower costs, non-uniform coverage, extended detection-to-repair cycles, and an inherent inability to scale across the dense road networks of rapidly growing cities. Sensor-equipped road-survey vehicles and ground-penetrating radar units overcome some of these limitations but are financially out of reach for most municipal bodies in developing countries.

Consumer smartphones now embed a rich suite of micro-electromechanical system (MEMS) sensors—including three-axis accelerometers, gyroscopes, and GPS receivers—that collectively capture fine-grained information about vehicle dynamics as the handset travels inside or on a vehicle. The vertical-axis accelerometer, in particular, responds sensitively to the impulsive shock transmitted through the wheel-tyre-suspension chain when a wheel traverses a surface discontinuity. This physical coupling motivates the use of accelerometer data as a proxy for road-surface condition.

Machine learning classifiers have demonstrated the capacity to distinguish statistically separable vibration signatures corresponding to different road-surface classes without manual threshold specification. Random Forest ensembles are especially attractive for this domain: they are robust to sensor noise, resistant to overfitting on moderate-sized datasets, interpretable through feature-importance ranking, and compact enough for on-device deployment.

This paper presents FixMyPath, an integrated system that couples smartphone accelerometry with a Random Forest classifier to achieve real-time, orientation-invariant pothole detection. The primary contributions are: (1) a curated, balanced accelerometer dataset spanning three road-surface

categories collected under real Indian traffic conditions; (2) a magnitude-based feature-engineering strategy that removes sensitivity to handset mounting orientation; (3) a trained. Random Forest model achieving 94.3 % classification accuracy; and (4) a fully functional Android prototype supporting live detection, user alerting, and event logging.

The remainder of this paper is organised as follows. Section II surveys related work. Section III details the four-stage methodology. Section IV presents experimental results and comparative analysis. Section V concludes the paper with directions for future work.

II. RELATED WORK

Smartphone-centric road-condition sensing has attracted sustained research attention over the past fifteen years. Mohan et al. [1] introduced Nericell, one of the earliest systems to exploit mobile-phone sensors for simultaneous road and traffic monitoring. Their platform fused accelerometer and microphone streams to identify potholes, bumps, and hard-braking events, validating the fundamental premise that commodity handsets carry adequate sensing capability for infrastructure monitoring. A key constraint of Nericell was its reliance on heuristic thresholds, which required manual recalibration for different vehicle types and mounting configurations.

Mednis et al. [3] conducted a comparative evaluation of threshold-based algorithms—Z-THRESH, Z-DIFF, and STDEV—on accelerometer data collected from vehicle-mounted Android smartphones. Their analysis revealed that fixed-threshold methods are sensitive to road-surface variability, vehicle weight, and suspension stiffness, motivating the shift toward learned classifiers. Eriksson et al. [6] extended the detection problem to a broader range of road anomalies and investigated map-based aggregation of individual detection events to filter false positives, an idea that informs the crowdsourcing roadmap of FixMyPath.

Kwapisz et al. [2] established a precedent for machine-learning-based activity recognition from cell-phone accelerometers, reporting high classification accuracy for walking, jogging, and stair-climbing using decision-tree and naïve-Bayes models. Their methodology—windowed feature extraction followed by supervised classification—translates naturally to road-surface categorisation, as vibration patterns associated with distinct surface types exhibit comparable temporal structure.

Sharma et al. [5] applied ensemble machine learning to smartphone-based road monitoring and reported accuracy improvements over threshold baselines, corroborating the advantages of data-driven approaches. However, the scope of that work did not extend to a deployable mobile application. The Scikit-learn library [7], which underpins

the training pipeline in this study, provides reproducible implementations of Random Forest and cross-validation utilities that facilitate fair benchmarking.

Taken together, the literature underscores two persistent gaps: (a) most systems remain research prototypes without integrated mobile deployment, and (b) orientation dependence of raw axis readings limits generalisability across mounting configurations. FixMyPath directly addresses both gaps through magnitude-based feature engineering and a production-ready Android application.

III. METHODOLOGY

The FixMyPath pipeline comprises four sequentially dependent stages: data collection, preprocessing and feature engineering, model training and evaluation, and mobile application development. Figure 1 (architecture diagram) illustrates the end-to-end information flow.

A. Data Collection

A Samsung Galaxy A52 smartphone was secured to the handlebar of a bicycle using a rigid mount to minimise relative motion between the handset and the vehicle frame. Accelerometer readings along three orthogonal axes (ax, ay, az) were sampled at 50 Hz using a custom Android logging application. Data acquisition traversed three operationally distinct surface categories:

- Normal Road – smooth asphalt exhibiting low-amplitude, low-frequency vibrations.
- Speed Breaker – engineered road humps producing characteristically broad, moderate-amplitude transients.
- Pothole – irregular surface depressions generating sharp, high-amplitude impulses.

Collection routes spanned multiple urban roads in Nagpur, Maharashtra, under representative daytime traffic conditions to capture environmental variability. Ground-truth labels were recorded concurrently by an observer with direct line-of-sight to the road surface. The final dataset comprises approximately 30,000 samples distributed uniformly across the three classes, ensuring that classifier performance is not artificially inflated by class imbalance.

B. Preprocessing and Feature Engineering

Raw readings were first screened for outlier values arising from device handling events—such as placing or repositioning the handset—that are unrelated to road conditions. A sliding-window segmentation scheme with a window length of 10 samples and 50 % overlap was applied to impose temporal locality and smooth transient noise. For each window, a resultant-acceleration magnitude M was computed as:

$$M = \sqrt{(ax^2 + ay^2 + az^2)}$$

The scalar M captures total vibration intensity independently of handset orientation, eliminating the need for rigid mounting conventions and broadening practical applicability. The final feature vector per sample contains four elements: $\{ax, ay, az, M\}$. All features were normalised to the $[0, 1]$ interval via min–max scaling, a step that stabilises gradient-based tuning procedures and ensures equitable feature contribution.

C. Model Training

A Random Forest classifier was selected based on its documented resilience to sensor noise, its capacity to provide feature-importance diagnostics, and its computationally lean inference footprint. Training was conducted in Python 3.9 using Scikit-learn [7]. The dataset was partitioned into 80 % training and 20 % test subsets via stratified random sampling to preserve class proportions in both splits. Optimal hyperparameters were identified through 5-fold stratified cross-validation on the training partition; the final model employs 100 decision trees and a maximum depth of 15 nodes per tree. The serialised model (via pickle) is packaged with the Android application and invoked through a lightweight Python-based inference service.

D. Android Application

The companion Android application was developed in Java within Android Studio. The `SensorManager` API streams accelerometer readings at 50 Hz to an in-app buffer. Each completed window is forwarded to the inference module, which computes M , constructs the feature vector, and queries the trained model. A Pothole classification (class index 2) triggers a red-banner visual alert and an auditory notification, enabling the rider to exercise caution without diverting attention from the road. The application additionally persists a timestamped log of pothole-detection events to local storage, supporting retrospective route analysis and forming the data substrate for future crowdsourced reporting.

IV. RESULTS AND DISCUSSION

Model evaluation was conducted on the held-out test partition of 6,000 samples. Table I summarises precision, recall, and F1-score for each class together with overall accuracy.

TABLE I. Classification Performance of the Random Forest Model

Class	Precision	Recall	F1-Score
Normal Road	0.97	0.96	0.96
Speed Breaker	0.92	0.91	0.91
Pothole	0.95	0.94	0.94
Overall Acc.	94.3 %	—	—

The classifier achieved the highest F1-score on the Normal Road category (0.96), where repetitive low-amplitude vibrations yield a compact, well-separated cluster in feature space. The Speed Breaker class recorded a marginally lower recall of 0.91, attributable to occasional overlap between mild pothole impulses and shallow speed-breaker profiles—a boundary condition that additional training samples could resolve. Pothole detection, the most safety-critical class, attained a balanced F1-score of 0.94, confirming that the magnitude feature provides a reliable discriminative signal for impulsive events.

Live trials across diverse Nagpur road segments validated real-world detection fidelity. The Android application sustained a mean per-window inference latency of approximately 18 ms, comfortably beneath the 200 ms threshold beyond which users perceive notification delay as disruptive. Continuous accelerometer sampling consumed roughly 4 % of battery capacity per operational hour, rendering prolonged background monitoring practical for typical urban commutes.

Comparative assessment against Nericell [1] and the threshold-based schemes of Mednis et al. [3] reveals two substantive advantages of FixMyPath. First, the data-driven classifier generalises across vehicle types and mounting configurations without manual recalibration, because the orientation-invariant magnitude feature abstracts away device-attitude variability. Second, the FixMyPath Android prototype offers an end-user interface—real-time alerts, event logs—that prior research prototypes did not provide, bridging the gap between laboratory validation and field deployment.

Residual false positives were predominantly associated with coarse gravel surfaces, which were absent from the training corpus. Expanding the dataset to encompass diverse pavement materials—including cobblestones, laterite roads, and worn bituminous surfaces—is expected to mitigate this limitation. Additionally, fusing GPS coordinates with detection events would enable spatial clustering of reports, filtering spurious isolated detections and constructing georeferenced pothole maps for municipal maintenance authorities.

V. CONCLUSION

This paper presented FixMyPath, a smartphone-accelerometer-based road-surface monitoring system that integrates a trained Random Forest classifier with a fully functional Android application. Vibration data collected across three surface categories—normal road, speed breaker, and pothole—were processed into orientation-invariant magnitude features, enabling robust classification irrespective of handset mounting position. The classifier achieved an overall accuracy of 94.3 %, with per-class F1-

scores confirming reliable discrimination across all categories. The companion application performs inference at a mean latency of 18 ms and sustains low battery overhead, making continuous passive monitoring feasible during everyday commutes.

The proposed framework offers a cost-effective, scalable complement to conventional road-inspection workflows. By transforming the ubiquitous smartphone into a pothole sensor, FixMyPath enables large-scale, citizen-driven data collection that could supply municipal agencies with timely, high-resolution road-condition intelligence at negligible cost.

Future work will pursue four directions. First, GPS integration will be incorporated to attach geographic coordinates to each detection event, enabling spatial aggregation and the construction of city-scale pothole heat maps. Second, the training dataset will be expanded to encompass a wider variety of vehicle categories—motorcycles, auto-rickshaws, and cars—and additional pavement types prevalent across India. Third, deep learning architectures, particularly Long Short-Term Memory (LSTM) networks, will be evaluated as potential replacements for the Random Forest model to leverage temporal dependencies in the vibration signal. Fourth, a cloud-based dashboard will be developed to aggregate crowdsourced reports, apply spatial clustering algorithms to filter noise, and present decision-ready maintenance recommendations to road authorities.

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