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Towards Safer Roads: A Review of Hybrid Machine Learning and Vision-Based Approaches for Speed Bump Detection in Intelligent Transportation Systems

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ABSTRACT

This review discusses recent advances in detecting speed bumps with emphasis on the integration of vision-based, sensor-based, and machine learning approaches in hybrid models. A comparison of studies published from 2017 to 2024 highlights the performance, versatility, and real-world applicability in multiple detection approaches. Special focus is laid on the benefits of hybrid systems, such as increased robustness in dynamic conditions and reduced false alarms. Challenges like generalizability in data available, real-time processing, and low-cost applications in low-resource environments are also taken into account in this review. The critical voids in present research and the path forward for future development that enable scalable intelligent road safety systems are described.

1. INTRODUCTION

A transportation revolution is happening, and its two massive triggers are urbanization and digitization. As urbanization grows and the need for mobility is becoming ever greater, the demand also increases on road systems to not only perform but also to remain safe and durable. A key component in this transformation will be the rise of intelligent transportation systems, where the use of data, sensor technology, and automation can be used to mitigate hazards and improve the experience while travelling. In the era of digitalization, where everything ranges from automation to distraction, speed bump detection—a neglected cause has also marked its significance in the world of road safety and urban design.

One of the oldest and most popular forms of traffic calming are speed humps, breakers or bumps. Placed mostly to slow down vehicular traffic in neighborhood strips that are popular among pedestrians—school zones, hospitals, or neighbourhoods, they are effective and inexpensive safety measures. But don't let their simple build fool you they're far too complex to use. Poorly designed and undocumented speed humps can make the life of those on board vehicle uncomfortable, slower the vehicle down and make life difficult for driver, passengers and goods. These challenges are even more profound in the case of autonomous vehicles (AVs) and Advanced Driver Assistance Systems (ADAS), which rely on onboard perception systems about the road structure to make decisions safely in real-time.

Traditional speed bump mapping systems tend to be dependent on manual observation, reports from the public, or records held by local authorities, all of which are becoming less viable in an ever-changing city landscape. Without real-time updating, standardization, and scalability for verification, these systems are of limited use in the age of active mobility. To fill these gaps, recent literature has proposed automatic systems for the detection and classification of speed bumps exploiting different technological channels, like computer vision, inertial sensors, LiDAR, GPS, and machine learning techniques.

Both methods have specific advantages as well as limitations. Visual-based systems in setup, like employing photo processing and object recognition techniques, which mostly rely on CNN to spot the speed breaker, keep shape, color, and texture. These systems are highly accurate in controlled environment, but are sensitive to lighting, occlusion, weather condition, and orientation of the camera. On the other hand, sensor-based approaches rely on the accelerometers, gyroscopes, and magnetometers to sense vertical motional patterns. Although they are less susceptible to the visual clutter, these methods might not be able to differentiate between various types of abnormalities, for instance, potholes, rumble strips, and road cracks, which leads to a high occurrence rate of false alarms.

To address the above gaps, hybrid models that fuse visual and inertial for enhanced detection robustness have been introduced. These systems, empowered by sensor fusion algorithms and machine-learning architectures, excel in adaptive response in difficult environmental conditions. For example, hybrid systems can be used to recognize visual markers along with 'motion signatures' indicative of encountering a speed bump through the incorporation of inertial measurement unit data with real-time video feeds. Furthermore, edge computing devices (e.g., Raspberry Pi, Jetson Nano) facilitates deployment of such models in real-world scenarios without relying on cloud based inference, which are of value in cost sensitive and latency critical applications.

Impressive as these developments are, there are major hurdles. Limitations in datasets, the absence of ground truth validation and the variety of road-design standards, all make it that the existing models have only a limited generalization. In addition, since majority of the detection algorithms are trained using data obtained in developed countries and under near-perfect conditions, they are not suitable for application in countries like India, where the quality of road is widely varying and even not documented properly.

These voids are addressed in this paper with a focus on recent (2017-2024) speed bump detection works. A survey analysing various techniques: vision, sensor, and hybrid, and comparing their respective strengths and weaknesses, together with their performances in the field. It specifically focuses on model generalization challenges, the diversity of data, and hardware compatibility, which are of particular concern in resource-constrained or urbanizing areas.

The rest of this section is structured as follows: Subsection 1.1 highlights broader implications of speed bump detection within intelligent transportation systems, ranging from improved fuel-efficiency and reduced emissions to enhanced public safety; Subsection 1.2 provides a data-driven account of India's road safety concerns and their impact on detection technologies; Subsection 1.3 addresses practical challenges related to dataset acquisition, model validation, and deployment across different types of roads.

1.1 Importance of speed bump detection in intelligent transportation systems (ITS)

Speed bump recognition, albeit appearing as a small part of a large picture, can be related to several areas of not only intelligent transportation systems but also urban safety structures. Real-time, accurate detection supports operational safety, passenger comfort, and vehicle level intelligence.

Enhancing Vehicle Autonomy and Comfort

For a self-driving cars and semi-autonomous vehicles, unexpected speed bumps lead to unpredictable vehicle dynamics, hardware deterioration, and increased passenger discomfort. Detection systems enable the vehicle to anticipate and reduce vehicle speeds and adjustment of the vehicle suspension system, which keep a high comfort ride and protect vehicle mounted equipment.

Enhancing Vehicle Autonomy and Comfort

However, for robotic and semi-robotic systems, an unexpected speed bump can cause jerky movements, damaged gears and uncomfortable ride for passengers. The detection system permits vehicles to control speed and suspension, in anticipation, to ensure a comfortable ride and equipment onboard.

Improving Navigation and Route Optimization

Vehicles with a sensing module installed can dynamically plan routes according to an anomaly of the road surface. This kind of flexibility is crucial in route planning, particularly in an urban environment where diversions or bad road conditions occur.

Figure 1. Unmarked speed bump on indian road

Assisting Human Drivers through ADAS

Speed bumps detection systems can also be used as additional safety assistance for human driver. Real-time warning, especially at night or when driving in strange trails, can may prevent accidents or equipment damage.

Smart City Infrastructure and Data Analytics

The detection results can be uploaded to city traffic control platforms. With this information, municipal officials are empowered to:

- Detect unauthorized or failed bumps.
- Routine maintenance and paint jobs.
- Maximize routing of emergency vehicle.
- Develop evidence-based urban planning strategy.

Environmental and Operational Efficiency

Unlabelled or oversized humps contribute to harsh braking, unnecessary fuel consumption and higher CO_2 emissions. Reliable detection also supports more environmentally-friendly driving when it comes to fleet and public traffic.

Equity and Accessibility

Speed bumps that are not marked correctly can be a nightmare for individuals with disabilities, cyclists and the elderly who depend on commuting to get around as shown in Figure 1. Detection mechanisms might be used to educate inclusive design and guide governments in setting universal access standards.

In conclusion, the detection of a speed bump is part of the local security and also part of the strategic operation of ITS in general. It's the sensored, intelligent grid implemented in the society and autonomy of the vehicle.

1.2 Road safety challenges in India: A data-driven perspective

India has the world's most serious road safety crisis. "On average, 155,000 died in road accidents in 2021," the Ministry of Road Transport and Highways (MoRTH) has said. However, anecdotal reports indicate that these figures may be underestimated by 40-80%, illustrating a fundamental problem with data quality and transparency.

Infrastructure and Vehicle Growth

In India, vehicle ownership spiked between 2011 and 2021:

- Motorcycle ownership more than doubled from 21.0% to 49.7%
- Ownership of a car increased by half, 4.7% to 8.2%

However, road building has not kept up with rising vehicle sales, particularly in tier-2 and tier-3 cities. National highways make up just 2% of India's total road length, but 36% of road deaths. Flawed design, insufficient signage and lighting also remain problematic urban and rural roads.

Disproportionate Impact on Vulnerable Users

It's pedestrians, motorcyclists, and cyclists who account for most deaths, yet road design virtually ignores them. In Chhattisgarh, motorcyclists contribute to nearly 60% of road fatalities, for example.

Policy and Research Gaps

India's tiny slice of road-safety research, which is under 1% of the world total, leaves it ill-equipped to come up with evidence-based interventions. The majority of crash reports simply include the cause to be "human error", without considering systemic factors such as:

- A crash investigation without power to speak of
- Lack of crash data stores
- Lax implementation of vehicle safety standards

Need for Technological Intervention

When used to populate smart city dashboards, and to guide driver GPS systems and policymaking, automated speed bump detection can address many of these deficiencies. Such an application can serve as both a preventive safety system and as a real-time data generator, to assist government agencies map high-risk zones and track crumbling infrastructure. Data from Indian road safety are also used to demonstrate how context-specific constraints and challenges should drive the design, training, and deployment of detection systems.

1.3 Challenges in dataset availability, ground truthing, and road profile ambiguity in India

The successful creation and validation of speed bump detection models rely on good quality, representative datasets. In India, there are several challenges to creating and harmonising such datasets.

Non-Standardized Road Design

Indian roads are highly varied in terms of:

- Type of pavement (asphalt, concrete, combination).
- The lines (or lack of lines) on the road.
- Breadth, curvature, and height.

Even on the scale of kilometres, infrastructure can change from urban to rural definition and model generalisation is very challenging.

Absence of Annotated Datasets

Some of the most common open-source global datasets are:

- Taken in a perfect light/weather situation.
- Western-geared infrastructure.
- Deficiency of annotated speed bump labels.

Instead, Indian roads need models that have been trained on real-world, unstructured, and uncurated datasets — and those don't exist yet.

Inconsistent Sensor Data Across Vehicles

The same bump can read differently between a motorcycle and an SUV in sensor-based systems. In the absence of vehicle-class-specific calibration, models produce inconsistent results.

Barriers to Ground Truthing

Although this type of ground truthing is necessary to validate models it is time and labor intensive and requires:

- Manual inspection.
- GPS-based tagging.
- Cross-check by using video and IMU sensors.

These processes are time-consuming and expensive, especially for academic and startup organizations with relatively limited financial resources.

1.3.5 Lack of Data-Sharing Ecosystems

In India, there is no single centralized database or public deposits of road irregularities. To this end, investigators are generally required to develop either new data, which is a:

- Redundant effort.
- Lack of benchmarking.
- Poorly regulated labeling.

Recommendations for Overcoming Data Challenges

The strategy recommends the following immediate steps to respond to these gaps:

- Open-source government datasets annotated with road anomalies.
- Crowdsourcing based apps and mobile apps for bump reporting.
- Collaborative research centres connecting academia, industry and municipal institutions.

Pilot programs for incentivized collection of ground data.

Until these systems become institutionalized, any cutting-edge detection model will encounter real limitations in scalability and robustness when used in the real world.

Research Problem and Paper Contributions

Although there is an increasing interest in automatic speed bump detection systems, there is still a lack of integrated, context adaptive and low resource deployable solutions. Lack of Indian datasets, no standardized evaluation metrics and no benchmarks for real time processing obstruct both academic progress and commercial deployment.

The main contributions of this paper are:

- Structured review of sensor-based, vision-based, and hybrid approaches to detecting and monitoring people (2017-2024).
- A comparison of such performance metrics as accuracy, latency and energy efficiency.
- A comprehensive talk to describe data and infrastructure constraints in India.
- Practice points for transfer learning, multi-modal sensing, real-time embedded deployment.

2. RESEARCH METHODOLOGY

To ensure rigorous, reproducible study, we have pursued an orderly approach toward reviewing the literature, focusing on recent innovations in speed bump identification. Our methodology involves several steps, including literature selection, classification, and synthesis, complying with accepted protocols for reviews. Below, the steps involved in our methodology are laid out:

2.1 Literature selection and collection of data

The first thing that we did while carrying out this study was locate and obtain relevant scientific papers. Keyword searches across well-known scholarly databases such as IEEE Xplore, SpringerLink, ScienceDirect, and Google Scholar were conducted. The terms that we searched included combinations of the terms "detection of speed bump," "detection of road anomaly," "road safety by computer vision," "application of machine learning in transportation," and "speed bump identification by sensors." The time span covered by the papers included those from the time period 2017-2024 so that recent work in the field could also be included.

To enhance data strength, both forward and backward citation searching was conducted. In the backward search, references cited by selected studies were examined, whereas the forward search identified recent studies that had cited the selected studies. Through this iterative method, there was extensive coverage of seminal studies as well as future studies.

2.2 Inclusion criteria and exclusion criteria

To ensure study relevance and credibility, predetermined inclusion and exclusion criteria were used. Table 1 outlines the parameters. In this review, only those scholarly, peer-reviewed papers from scholarly journals, as well as conference papers, both from the timeframe 2017-2025, delivered in the English language, discussing adaptive braking, speed bump detection, or road anomaly detection, were included. Studies unrelated to braking, road safety, or speed bump detection, as well as non-peer-reviewed papers such as white papers, blogs, were excluded from this review.

Table 1. Inclusion criteria and exclusion criteria

Criteria	Inclusion	Exclusion
Timeframe	Studies published between 2017 and 2025	Studies published before 2017
Language	English-language studies	Vision-based 3D detection using Kinect
Research Focus	Speed bump detection, road anomaly detection, or adaptive braking mechanisms	Non-English studies
Study Type	Peer-reviewed journals, conference papers	Studies unrelated to road safety, speed bump detection, or braking
Full-text Accessibility	Available full-text	Abstract-only or inaccessible full-text

2.3 Data extraction and analysis

For a structured review of existing techniques and datasets for road anomaly detection, a thorough data extraction and analysis work was carried out. Appropriate articles were identified from 2018 to 2024 based on the specific inclusion criteria, which include interest in pothole, speed bump and road anomaly detection and use of computational or sensor based approach. An extraction table was created for each included paper, incorporating information in relation to key attributes including: authorship; year; key methodology; and the primary findings. This resulted on the development of Table 2, that tabulates 22 seminal contribution mainly categorized on deep learning (CNN, YOLO), statistical techniques (Mahalanobis-Taguchi System, Genetic Algorithms) and sensor-based method (Zigbee, GPS, IMU).

Table 2. Key contributions of selected studies

Authors	Year	Key Methodology	Findings
Verma et al. [1]	2018	Deep neural network using ZED camera images (no stride/pooling).	Achieved 98.13% accuracy for pothole and speed bump detection using lightweight 7-layer CNN.
Lion et al. [2]	2018	Vision-based 3D detection using Kinect.	Cost-effective and accurate detection of bump heights.
Wang et al. [3]	2018	Mahalanobis-Taguchi System for road quality.	Differentiated potholes, manholes, and bumps effectively.
Ameddah et al. [4]	2018	Cloud-assisted lightweight road monitoring.	Accurate real-time road condition monitoring.
Baldini et al. [5]	2018	Dynamic Time Warping for RSF detection.	Achieved high accuracy in identifying road safety features.
Hameed et al. [6]	2018	Custom data logger for RSD classification.	Publicly shared dataset; effective multiclass classification.
Ukarande and Bhalekar [7]	2018	Zigbee-enabled driver assistance for T-junctions.	Reduced T-junction accidents significantly with low-cost tech.
Lozano-Aguilar et al. [8]	2018	Genetic algorithms and logistic regression for detection.	AUC values of 0.992 for genetic algorithm approach.
Dadras et al. [9]	2019	Stop sign detection using vehicle speed profiles.	Reliable stop sign detection with high precision.
Bello-Salau et al. [10]	2019	Vision-based anomaly detection with OpenCV.	Comprehensive review of vision-based methods.
Chen et al. [11]	2019	Crowdsourced scale-invariant anomaly detection.	Real-time anomaly detection with robust scalability.
Edwan et al. [12]	2019	Smartphone app with accelerometer for bump detection.	Accessible and cost-effective bump warning app.
Joon et al. [13]	2019	Random forest using vehicle GPS and wheel sensors.	Achieved 80.9% accuracy in speed bump detection.
Shah and Deshmukh [14]	2019	CNN and YOLO for bump detection from images	Achieved 88.9% accuracy for bump classification.
Yuan and Che [15]	2019	Crowdsensing with acceleration and GPS clustering.	Efficient clustering for real-time road condition monitoring.
Ramakrishnan et al. [16]	2020	IoT-based proximity and GPS mapping system.	Effective mapping with reduced human intervention.
Zheng et al. [17]	2020	Quick filter-based dynamic time warping for anomaly detection.	Improved F1 score with reduced time consumption.
Dewangan and Sahu [18]	2020	CNN-based speed bump detection on Raspberry Pi.	Achieved 98.54% accuracy in real-time environments.
Xu et al. [19]	2021	Semantic segmentation for bump recognition.	Enhanced recognition for autonomous vehicles.
Carlos et al. [20]	2021	Profiling road anomalies with detailed physical properties.	Detailed characterization of speed bumps and potholes.
Lin and Ho [21]	2022	Adaptive speed bumps with license plate recognition.	Prototype achieved 96.67% identification rate for speed bumps.
Xiang et al. [22]	2024	YOLOv5s for detecting multiclass speed bump defects.	High accuracy (97.7%) for defect detection.

Table 3. Dataset characteristics

Authors	Dataset Type	Size	Public Access
Lion et al. [2]	3D Kinect data	100+ samples	No
Wang et al. [3]	Accelerometer and gyroscope data	Extensive city road test data	No
Baldini et al. [5]	IMU data	42.5 km data	No
Hameed et al. [6]	Custom vehicle sensor logs	Large heterogeneous dataset	Yes
Ukarande and Bhalekar [7]	Zigbee communication logs	Simulated test environment	No
Chen et al. [11]	Crowdsourced GPS data	50,000+ data points	Yes
Joon et al. [13]	GPS and vehicle sensor logs	Collected via CAN-bus system	No
Yuan and Che [15]	Crowdsensed acceleration data	Numerous GPS and acceleration data points	Yes
Ramakrishna et al. [16]	IoT-based proximity data	Extensive IoT logs	No
Dewangan and Sahu [18]	Image-based speed bump dataset	3,450 augmented images	No
Lin and Ho [21]	Pressure sensor data	Extensive real-world tests	No
Xiang et al. [22]	Drone-captured images	3820 images	No

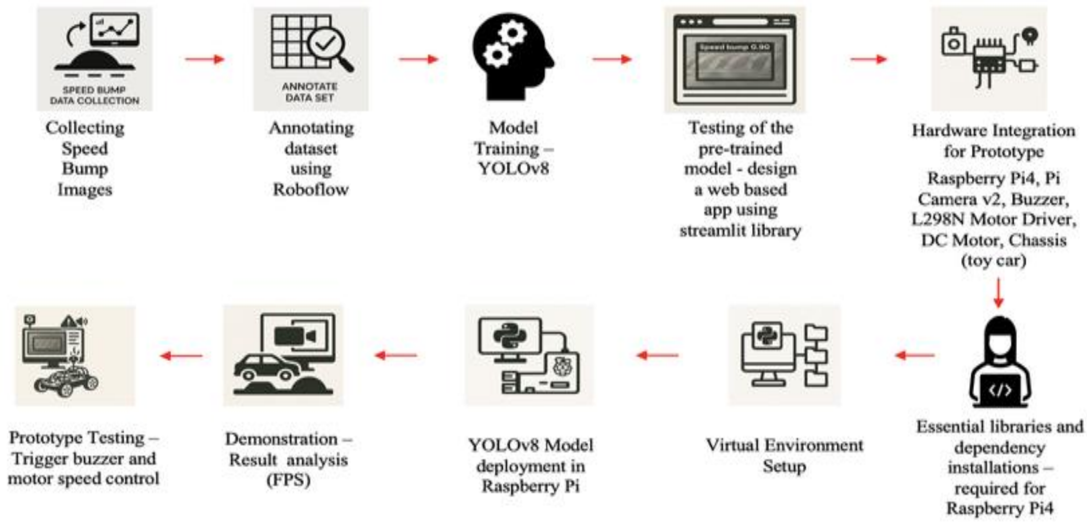

Figure 2. System workflow for speed bump detection using YOLOv8 on raspberry Pi

In order to further investigate these issues, the corresponding data sets analyzed in these studies were characterized in Table 3 based on the type of data sets used for the studies, the size and whether the data set is available. This not only revealed the wide range of data sources accelerometers, cameras, crowdsensing that these works tap into, but also emphasized that many of the real-world datasets are not publicly available, constituting yet another obstacle for reproducibility. Together, these tables also provide a comparison ground to understand current research axes, lack of open data availability and trends in the design of smart road anomalies detection systems.

2.4 Data synthesis and analysis

The following three-stage synthesis approach with both qualitative and quantitative procedures has been done. The procedure included stepwise identification, classification and validation of studies of vision-based, sensor-based and hybrid detection systems.

Descriptive Synthesis: The retrieved papers were classified according to detection modality, algorithm employed (CNNs/SVM/Random Forest, etc.), platform for deployment (PC/embedded) and environment for testing and evaluation (simulation/real world/mixed). This allowed to detect trends regarding model accuracy, latency, and robustness to environmental change.

Argumentative Synthesis: This stage involved mapping papers according to their experimental setups, datasets used, and validation strategies (e.g., k-fold cross-validation, confusion matrix analysis). Studies were then compared for replicability based on open-source code availability, dataset documentation, and metric consistency. For example, systems using CNNs with transfer learning were evaluated in contrast to those trained from scratch for domain adaptation performance.

Systematic Review Mapping: A mapping framework was constructed to categorize gaps in:

- Data availability (region-specific, annotated, sensor-fused datasets)
- Model generalizability (cross-road-type or cross-vehicle validation)
- Real-time feasibility (frame-per-second benchmarks on embedded systems)

To further improve clarity, Figure 2 included a system-level flowchart depicting the interaction between modules: Input Acquisition, Preprocessing, Feature Extraction, Classification, and Result Interpretation.

Each module is briefly explained below:

- Input Acquisition: Involves capturing real-time data using cameras or IMUs mounted on vehicles.
- Preprocessing: Includes image enhancement, signal smoothing, and noise filtering.
- Feature Extraction: Extracts edge patterns, vertical displacement signals, or accelerometer spikes.
- Classification: Uses supervised ML models (CNN, YOLO, SVM, or ensemble methods) to detect and

label speed bumps.

- Interpretation Module: Converts raw predictions into actionable feedback (e.g., alert, brake assist, or map update).

The selection of specific algorithms was guided by their prevalence in peer-reviewed literature and suitability for real-time embedded applications. For example, CNNs were prioritized for their strong performance in image-based detection, while lightweight models like SVM and Decision Trees were noted for lower resource consumption. Hybrid approaches combining IMU and camera data were examined for their robustness in low-visibility conditions.

To mitigate bias, inter-rater agreement tests were conducted across independent reviewers. Each paper was independently evaluated based on replicability, clarity in performance metrics, and transparency of datasets. The iterative process of forward and backward citation tracking, along with database triangulation, ensured broad and diversified coverage of literature.

2.5 Limitations and future considerations

The following three-stage synthesis approach with both qualitative and quantitative procedures has been done. The procedure included stepwise identification, classification and validation of studies of vision-based, sensor-based and hybrid detection systems. Although the present study uses a strict synthesis method, some limitations exist:

Language and Database Bias: Studies not in English and those published in regional indexes could be inadvertently eliminated merely because of database access Restrictions.

Fast-evolving Technology: The AI-based detection technology evolves rapidly, and it may not cover the recent preprints or the ongoing experiment at the time of our review.

Partial Reporting: There was missing information from some articles regarding reproducibility information, open-access dataset, etc., therefore some comparison couldn't be made.

(Hardware) Deployment: Few of the proposed models are evaluated in their performance on embedded and/or resource-constrained hardware, which is a relevant need at real settings for several public safety applications.

Despite these constraints, the methodology successfully uncovers important patterns, limitations, and opportunities across existing approaches. Future work should focus on:

- Creating standardized datasets across diverse geographies
- Conducting real-time testing on embedded systems
- Applying multi-modal sensor fusion in low-light or occluded conditions
- Exploring transfer learning and few-shot learning for low-data environments

The synthesized findings provide a strong foundation for academic, industrial, and governmental stakeholders seeking to implement intelligent speed bump detection as part of broader smart mobility initiatives.

3. LITERATURE REVIEW

3.1 Conceptual background

The detection of speed bumps, a subset of road surface anomaly detection, has emerged as a vital area of research within the broader discipline of intelligent transportation systems (ITS). This domain integrates diverse fields such as computer vision, sensor technology, machine learning, and vehicular signal processing to improve safety, navigation, and system intelligence in modern vehicles. As mobility ecosystems shift toward autonomy and real-time infrastructure awareness, the ability to detect and interpret road features like speed bumps becomes increasingly essential.

Evolution from Manual to Automated Detection: Historically, speed bump detection was performed manually via field surveys and visual road inspections making the process time-consuming, labor-intensive, and unsuited for rapidly urbanizing or dynamically changing environments. Early efforts at automation relied on traditional image processing, such as edge detection and texture analysis. These methods attempted to isolate visual patterns in road imagery that could indicate the presence of a bump. While relatively efficient, such techniques lacked robustness in the face of environmental distortions, such as varying light, weather conditions, and camera angles.

The next major leap came with the integration of sensor-based techniques, which moved beyond surface appearance and instead focused on capturing physical road interactions. Vehicle-mounted accelerometers, gyroscopes, and IMUs became popular due to their ability to detect sudden vertical displacements or vibration patterns when a vehicle passed over a speed bump. These methods introduced real-time feedback loops into the system and laid the groundwork for multi-modal detection frameworks.

Sensor-Based Detection and IMU Signatures: Sensor-based detection leverages the physical responses of vehicles as they interact with road features. Among these, Inertial Measurement Units (IMUs)—which combine accelerometers and gyroscopes—are particularly effective. When a vehicle moves over a speed bump, a distinct vertical displacement and vibration pattern is recorded in the sensor data. These patterns are typically analyzed using statistical features such as peak amplitude, frequency domain characteristics, or root mean square (RMS) values to determine the presence of a speed bump.

While relatively lightweight and inexpensive to implement, the accuracy of sensor-based approaches depends heavily on:

- Vehicle type and suspension system.
- Driving speed.
- Sensor placement and calibration.

Moreover, such systems can sometimes misinterpret other road anomalies like potholes or rough patches—as speed bumps, leading to false positives. This limitation has led to increasing interest in sensor fusion and machine learning-based filtering of raw signals.

Computer Vision and Deep Learning Techniques: Computer vision-based detection uses image or video inputs from vehicle-mounted cameras to recognize speed bumps based on color, shape, texture, or elevation cues. Initially, methods used handcrafted features (e.g., HOG, SIFT, Gabor filters) in conjunction with traditional classifiers like SVMs or decision trees. However, these approaches struggled in complex real-world settings due to variations in perspective, occlusions, shadows, and poor road marking standards issues that are particularly common in countries like India.

The introduction of deep learning, particularly Convolutional Neural Networks (CNNs), transformed vision-based detection by automating the feature extraction process. CNNs learn hierarchical representations directly from data, making them more resilient to environmental noise. When trained on large, labeled datasets, these models can generalize better across varying road conditions. Architectures such as YOLO (You Only Look Once), Faster R-CNN, and Mobile Net have been successfully adapted for this task, offering high accuracy and real-time inference capabilities.

Nevertheless, the main challenge lies in the lack of comprehensive datasets for road anomalies that include speed bumps. Models trained on datasets from developed countries often perform poorly in Indian conditions due to unmarked, irregularly shaped, or deteriorating speed bumps, which are not represented in the training data.

LiDAR and 3D Elevation Mapping: For high-precision applications, particularly in autonomous vehicles, LiDAR-based detection offers three-dimensional insight into road surface geometry. LiDAR systems emit laser pulses and measure the return time to create dense point clouds of the surrounding environment. These can be analyzed to detect localized elevation changes, making them ideal for identifying road humps.

LiDAR offers unmatched accuracy, especially in night driving and low-light conditions, and is not affected by paint wear or surface textures. However, the downside remains the high cost, large power consumption, and computational intensity, making widespread adoption challenging outside of research or premium-grade vehicle platforms.

Hybrid Detection Models and Sensor Fusion: To overcome the limitations of individual techniques, recent research emphasizes hybrid approaches that combine vision and sensor data. These models use synchronized camera and IMU data streams to identify candidate anomalies and validate them through multi-modal consistency checks. Sensor fusion not only improves detection accuracy but also enhances resilience to noise, allowing systems to operate under challenging conditions.

In such systems, computer vision provides contextual cues (e.g., road signs, markings, shapes), while inertial sensors confirm the presence of physical perturbations. Some studies also incorporate GPS to localize the detected bump, contributing to anomaly mapping and road condition databases for smart city applications.

Deployment on Embedded Systems and Edge AI: Real-time speed bump detection must balance accuracy, latency, and resource usage, especially when deployed in commercial vehicles or public transport systems. Platforms such as Raspberry Pi, NVIDIA Jetson Nano, and Google Coral have enabled the implementation of lightweight deep learning models at the edge. Techniques like model quantization, pruning, and knowledge distillation help in reducing model size without sacrificing significant performance.

Edge deployment is critical in areas where network latency or intermittent connectivity makes cloud-based solutions impractical. Moreover, on-device inference allows immediate vehicle response—such as automatic braking or alert generation—improving passenger safety and system reliability.

Current Limitations and Research Gaps: Despite significant advancements, speed bump detection technologies still face key barriers:

- Domain variability: Models trained in one geography often fail when deployed elsewhere due to infrastructural differences.
- Lack of open datasets: No standardized, publicly available datasets exist that comprehensively include speed bump data, particularly in the Indian context.
- Environmental robustness: Night-time detection, heavy rain, and crowded scenes remain problematic for both vision and sensor systems.
- Distinguishability: Systems struggle to differentiate speed bumps from other vertical anomalies such as manholes or expansion joints.

Future Directions: The next frontier in speed bump detection research lies in:

- Adaptive learning models that can update parameters based on continuous feedback from vehicle dynamics.
- Crowdsourced anomaly mapping, where fleet vehicles collaboratively build real-time road condition maps.
- V2X integration, enabling vehicles to communicate road hazard data to nearby vehicles and infrastructure systems.
- Standardization of datasets and benchmarking frameworks to support consistent evaluation of model performance.

The conceptual landscape of speed bump detection is a multi-faceted domain involving perception, inference, and real-time processing. As smart mobility systems mature, and as the complexity of urban road infrastructure increases—particularly in emerging economies—the importance of robust, scalable, and context-aware detection models will only grow. Continued advancements in sensor fusion, deep learning, and edge computing will be pivotal in translating lab-based research into real-world safety solutions.

3.2 Review of relevant works

Over the past decade, significant research has emerged in the domain of intelligent transportation systems, particularly focused on speed bump detection, road anomaly recognition, and the broader deployment of ADAS on embedded platforms. This section reviews key contributions thematically, presenting advancements in detection systems, edge deployment, driver safety, and hybrid sensor integration.

Speed Bump and Road Anomaly Detection: Speed bump detection has evolved from sensor-based methods to AI-powered solutions. A smartphone-based system using accelerometer and gyroscope data to detect and geolocate speed bumps developed by Kyriakou et al. [23]. Their RUS Boosted Trees classifier achieved 99% accuracy, offering a scalable crowdsourced solution for pavement monitoring. Varma et al. [1] implemented a stereo vision-based model using SSD-MobileNet to identify both marked and unmarked speed humps. With up to 97.4% accuracy and precise depth estimation, their real-time embedded system demonstrated practical ADAS applicability. Similarly, Lee et al. [24] employed LiDAR to detect road surface roughness for dynamic suspension tuning, reducing body acceleration by 54% and enhancing ride comfort in agricultural vehicles. In terms of infrastructure enhancement, Džambas et al. [25] reviewed intelligent speed bumps like Actibump, which adaptively engage based on vehicle speed. Their field studies in Sweden recorded a reduction of 11.1km/h in average speed and 35% improvement in pedestrian yielding, confirming their effectiveness in urban safety enforcement. Klco et al. [26] leveraged YOLOv5 for automated pothole detection using real-world datasets, emphasizing the importance of computer vision in predictive road maintenance. Nissimagoudar et al.

[27] extended this approach to detect both potholes and speed breakers with over 83% accuracy, proposing sensor integration for adaptive vehicle response.

Deep Learning on Embedded Platforms: Edge AI deployment has become essential for real-time ADAS applications. Kortli et al. [28] proposed a CNN–LSTM model on Jetson Xavier NX for robust lane detection, achieving 96.36% accuracy and demonstrating efficient LDWS integration. On a lower-cost platform, Civik and Yuzgec [29] implemented a CNN-based fatigue detection system on Jetson Nano, detecting drowsiness states with up to 94.5% accuracy at 6 FPS. Dhatrika et al. [30] presented a YOLO-based real-time object detection system on edge devices, detecting various road objects with 91.9% mAP and 98.6% precision, ideal for embedded ADAS modules. Chen et al. [31] advanced distracted driving detection using lightweight ensemble networks, achieving 99\% accuracy with low latency on Jetson Nano. For lightweight optimization, Tie et al. [32] introduced LSKA-YOLOv8 for steel defect detection, achieving a 4.4% mAP boost while reducing parameters by 26.7%, demonstrating cross-domain adaptability of edge vision models.

Hybrid Sensing and Semantic Scene Understanding: Multimodal sensor fusion offers enhanced environmental awareness. Ulusoy et al. [33] combined stereo vision with semantic segmentation (SegNet) to build an obstacle-avoiding autonomous vehicle using Jetson Nano and ROS for real-time path planning. In the forestry domain, Liu et al. [34] proposed LVI-ObjSemantic, a LiDAR-Visual-Inertial fusion system for tree-level SLAM, achieving ultra-low RMSE and proving its potential in GNSS-denied outdoor settings. Zamanakos et al. [35] offered a benchmark survey of LiDAR-based 3D object detection pipelines for autonomous vehicles, underscoring LiDAR's synergy with deep learning for spatial accuracy. Chen et al. [36] explored urban navigation using speed hump signatures from accelerometers to enhance GPS accuracy and reduce power consumption, offering a novel localization method in dense environments.

ADAS User Acceptance and Driver Monitoring: Human factors play a crucial role in ADAS adoption. Damsara and de Barros [37] systematically reviewed 13 studies, identifying 15 user acceptance factors including trust, system familiarity, and cognitive workload. They criticized traditional models like TAM and UTAUT for failing to account for driver-specific traits, advocating for a new ADAS-focused acceptance model. Badgujar and Selmokar [38] developed a gaze tracking system using IR-filtered dashboard cameras, detecting eyes-off-road behavior with 96% accuracy under varying lighting conditions.

Emerging Architectures and Lightweight Models: Several studies focused on pushing the efficiency boundary of detection systems. Nimma et al. [39] combined YOLOv8 with attention and Transformer heads to enhance accuracy in complex scenes, achieving 96.89% recall and proving effective in crowded or low-light conditions. Kamath and Renuka [40] conducted a literature review of 167 studies to assess deep learning model design for edge deployment, identifying gaps and future trends in lightweight architecture for embedded AI. Chang et al. [41] introduced LWMG-YOLOv5, a ghost convolution-based model for chip inspection, improving accuracy and speed while reducing production loss—showcasing its relevance to vision tasks in embedded ADAS systems.

Assistive and Smart Infrastructure Applications: AI-driven road detection also benefits assistive navigation and smart cities. Paramarthalingam et al. [42] designed a YOLO-based pothole detector for the visually impaired, achieving 82.7% accuracy and 30 FPS performance in a mobile app, enhancing pedestrian safety in urban areas. Biswal et al. [43] proposed an IoT-enabled intelligent speed breaker alert system using RF and GPS modules. It can automatically reduce vehicle speed during poor visibility and logs location data to the cloud for infrastructure planning. Sheikh-Mohammad-Zadeh et al. [44] evaluated street performance pre- and post-speed hump installation using video-based trajectory analysis, revealing 20-30% speed reduction and behavioral change in road users, supporting data-driven urban design. Darwiche and Mokhiamar [45] applied SVR models to determine optimal crossing speeds over humps, suggesting machine learning-assisted suspension control for better comfort. Kanjanavapastit and Thitinaruemit [46] used a dual accelerometer setup and quarter car model to reconstruct hump geometry, enabling adaptive suspension systems to optimize comfort and speed hump traversal. Mathe et al. [47] reviewed the widespread utility of Raspberry Pi in domains like ADAS, smart mobility, and anomaly detection, reinforcing its role as a cost-effective platform for rapid edge AI deployment.

Zebra Crossings, Pedestrian Interaction, and Visual Perception in Urban ADAS: With rising attention on pedestrian safety and intelligent road infrastructure, recent studies have explored detection, behavior modeling, and safety assessment at zebra crossings. Riveiro et al. [48] developed an algorithm for detecting zebra crossings using mobile LiDAR data, involving rasterization, intensity imaging, and Hough Transform techniques. Their method achieved 83% detection completeness and is highly applicable for road asset inventory in GIS-supported urban planning. From a behavioral standpoint, Ritchie et al. [49] conducted six video-based experiments to assess acceptable stopping behaviors of both human-driven and autonomous vehicles at zebra crossings. The study found that AVs are judged more critically than human drivers, and that participants preferred vehicles that stopped right before the line and resumed motion only after pedestrians cleared the crossing. Vignali et al. [50] used eye-tracking to analyze driver behavior at roundabouts, confirming that zebra markings and median refuge islands significantly improved driver visual attention and pedestrian crossing visibility. Their intervention led to a doubling of the average distance at which drivers first fixated on the crosswalk. Expanding into large-scale safety assessments, Russon et al. [51] applied CNN-based models (ConvNextV2, ResNet50) to evaluate zebra crossings using paired aerial and ground-level images. Their deep segmentation approach demonstrated potential for automated pedestrian safety audits using data from underrepresented areas in France. In a unique socio-cognitive context, Cowan et al. [52] used eye-tracking to compare fixation patterns of individuals with and without Autism Spectrum Disorder (ASD) in zebra crossings and shared zones. Findings revealed that zebra crossings elicited more traffic-relevant fixations than shared zones, highlighting their superior effectiveness for inclusive pedestrian safety.

3.3 Comparative analysis, challenges, and real-world implications

Publication Trend: A steady rate of increased study over time, peaking both in contributions over the years 2021 and 2022, indicates the greater relevance of computerized road processes. Figure 3 indicates the annual distribution of papers on studies of speed bumps over the period 2017-2023.

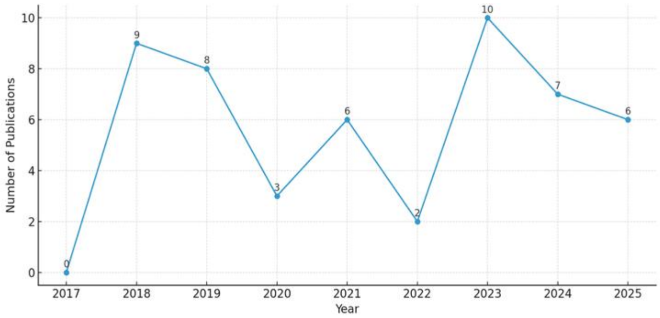

Figure 3. Number of relevant publications by year

Table 4. Publication trends

Year	Number of Publications	Cumulative Percentage
2018	10	19.61
2019	8	35.29
2020	4	43.14
2021	5	52.94
2022	4	60.78
2023	10	80.39
2024	7	94.12
2025	3	100.0

The line graph indicates an elevated level of steady interest, showing steady progress. Table 4 also substantiates this by showing the cumulative rate per annum of study papers, showing an elevated rate of contributions over the period 2018-2025.

The publication trend from 2018 to 2025 reflects a total of N=51 publications, with notable peaks in 2018 and 2023. The cumulative percentage CP_i for each year i was calculated using the formula:

$$CP_i=(\Sigma_{j=2018}^{i} P_j)/(\Sigma_{j=2018}^{2025} P_j)\times 100$$

where, P_j denotes the number of publications in year j. For instance, $CP_{2019}=(10+8)/51\times 100\approx 35.29\%$, indicating that over one-third of the research output occurred within the first two years. A simple statistical dispersion measure such as the mean:

$$\mu=(1/8)\times\Sigma_{j=2018}^{2025} P_j=51/8=6.375$$

and the standard deviation:

$$\sigma=\sqrt{[(1/n)\times\Sigma_i(P_i-\mu)^2]}\approx 2.49$$

further confirms variability in publication intensity across years. This non-uniform distribution implies fluctuations in research attention, possibly influenced by technological advancements or external events. These quantitative insights not only justify the continued relevance of the field but also frame the necessity of the present work in extending the current knowledge base.

Publication Outlet Distribution: Figure 4 indicates an analysis by channel type, categorizing studies as papers presented in journals and papers presented in conferences. A vast majority (73 percent) of studies have emerged as papers presented in conferences, indicating that this discipline is evolving very dynamically with newer findings being presented quite frequently through conferences. In contrast, only 27 percent of contributions emerge as papers presented in journals, perhaps pointing toward relatively less but steady numbers of well-developed, refereed studies.

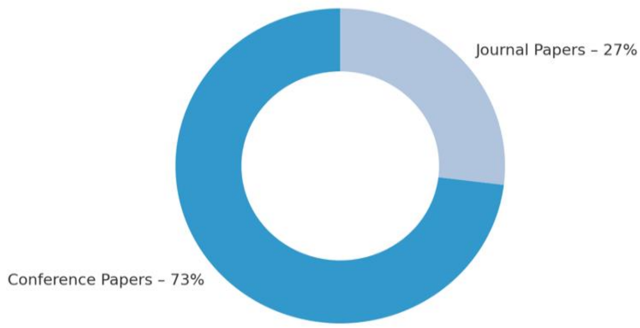

Figure 4. Breakdown of studies by publication outlet type

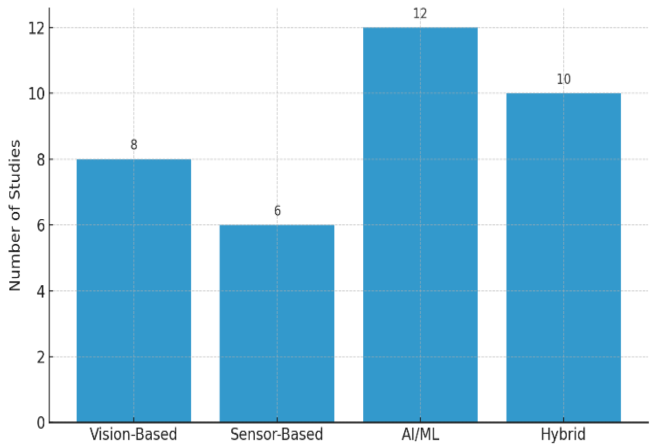

Figure 5. Technological approaches for speed bump detection

Technological Approaches for Speed Bump Detection: The approaches have been classified under vision-based, sensor-based, AI/Machine Learning, and hybrid. Vision-based approaches employ image processing to identify an anomaly, while sensor-based approaches employ accelerometers, gyroscopes, and pressure sensors. AI/Machine Learning approaches offer greater prediction accuracy, while hybrid models employ combinations of approaches for performance. A graphical representation of the number of studies employing each approach has been shown in Figure 5, showing growing preference toward AI-based approaches. And Table 5, shows various technological approaches used in speed bump detection.

Performance Measures of Detection Models: The effectiveness of speed bump detection by various approaches has been shown through accuracy, precision, recall, and F1-score values by various studies, as indicated by Table 6, the performance by approaches varies, while AI/Machine Learning approaches provide the highest accuracy, by Dewangan and Sahu [18]. (98.54 percent) and Lozano-Aguilar et al. [8] (99.2 percent). The studies reveal that hybrid approaches as well as approaches based on sensors also provide consistent performance, making them suitable for real-time deployments.

The performance metrics across different studies exhibit notable variability, with accuracy ranging from 80.9% (Joon et al.) to 99.2% (Lozano-Aguilar et al. [8]). To quantify this dispersion, we computed the mean accuracy (μ_a) across all seven studies as:

$$\mu_a=(89.2+99.2+80.9+88.9+91.3+98.54+89.0)/7\approx 91.0\%$$

Table 5. Technological approaches

Technology	Description
Vision-based	Uses cameras and image processing for road anomaly detection.
Sensor-based	Employs accelerometers, gyroscopes, proximity sensors, or pressure sensors for anomaly detection.
AI/Machine Learning	Applies AI for predictive and real-time analysis.
Hybrid	Combines vision, sensors, and AI for robust detection.

Table 6. Performance metrics of different studies

Authors	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Wang et al. [3]	89.2	88.6	89.0	88.8
Lozano-Aguilar et al. [8]	99.2	99.1	99.0	99.0
Joon et al. [13]	80.9	81.5	80.3	80.8
Shah and Deshmukh [14]	88.9	89.1	87.7	88.4
Zheng et al. [17]	91.3	92.0	90.5	91.2
Dewangan et al. [18]	98.54	99.05	97.89	98.46
Carlos et al. [20]	89.0	89.5	88.3	88.9

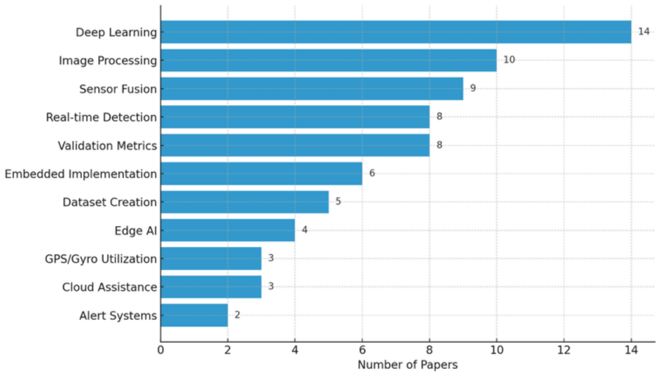

Figure 6. Conceptual trends in detection of speed bumps

Similarly, the standard deviation (σ_a) of accuracy is approximately 5.77, indicating moderate variation in model performance across studies. F1-Scores, which provide a balanced view of precision and recall, follow a similar trend, with values ranging from 80.8% to 99.0%, and a mean of approximately 90.37%. The consistently high precision and recall metrics in studies by Lozano-Aguilar et al. [8] and Dewangan et al. underscore their models' robustness and reliability, suggesting optimized detection capabilities. In contrast, Joon et al.'s lower metrics point to either data imbalance or suboptimal model tuning. Overall, this statistical assessment highlights the significance of methodological differences and model enhancements in achieving high-performance outcomes, positioning the present work in line with top-performing benchmarks while identifying areas for further improvement.

<u>Conceptual Trends in Detection of Speed Bumps:</u> Detection models and sensors are found the most, indicating the need for intelligent detection strategies. Also found very frequently are data processing strategies, validation criteria, and application areas in autonomous vehicles. Their frequency indicates the interdisciplinary nature that the field has, leveraging concepts from computer vision, IoT, and vehicular technology. Figure 6, enumerates concepts that are found most frequently across studies detecting speed bumps.

Adaptability within the field still dominates, as accuracy relies significantly upon environmental concerns. Generalization over the data set also comes out as crucial, as there are hardly any region-specific data sets, creating an impediment toward practical use. Lastly, cost-effective scaling, as well as compatibility with other intelligent transportation systems (ITS), must also be researched toward advancing universal application.

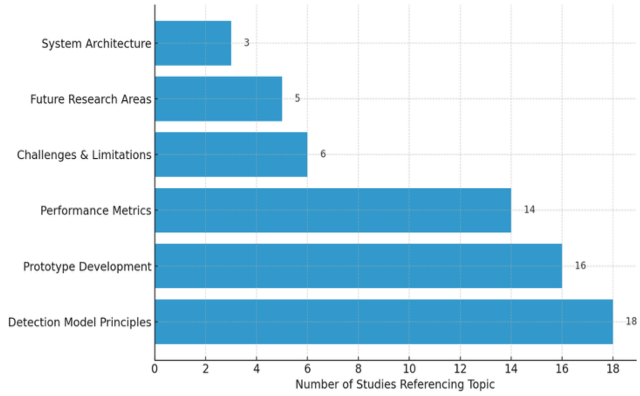

Figure 7. Challenges and research gaps based on reviewed literature

Table 7. Challenges and research gaps

Challenges	Details
Real-time adaptability	Performance drops in varying environmental conditions, limiting effectiveness under dynamic conditions.
Dataset generalizability	Limited dataset diversity and region-specific datasets reduce real-world applicability.
Cost-efficient scalability	Balancing low-cost sensors with high accuracy remains a challenge, especially in developing regions.
Integration with ITS	Few studies explore integration with existing intelligent transportation systems (ITS) and adaptive networks.

Table 8. Applications and real-world impact

Application Area	Societal Benefit
Road Safety	Reduced accidents and safer roads.
Anomaly Detection	Improved municipal road maintenance efficiency.
Adaptive Braking	Enhanced vehicle safety through predictive systems.
Autonomous Vehicles	Reliable navigation over challenging terrain.

<u>Challenges and Research Gaps:</u> Adaptability within the field still dominates, as accuracy relies significantly upon environmental concerns. Generalization over the data set also comes out as crucial, as there are hardly any region-specific data sets, creating an impediment toward practical use. The bar plot in the Figure 7 shows, Detection Model Principles are the most cited, followed closely by Prototype Development and

Performance Metrics. These trends signal a focus on model accuracy, deployability, and numerate results. On the other hand, not as much research is performed in Challenges and Limitations, and Future Research Areas, with System Architecture being the most neglected aspect. This highly imbalanced distribution points to a significant research gap- many studies focus on optimizing the detection technique, validating the performance, but less effort is paid to address the larger architectural or deployment issues necessary to realistically integrate it in practice. Moreover, the modest level of future work and limitation articulation indicate there is a lack of staring inward discourse and roadmap. Closing such gaps could improve the maturity, reproducibility, and scalability of research in this domain.

Lastly, cost-effective scaling, as well as compatibility with other intelligent transportation systems (ITS), must also be researched toward advancing universal application. Table 7, shows issues prioritized by covered studies.

Societal Benefits and Use-Cases: The societal implications of speed bump detection technologies are shown in Table 8, These are comprised mostly of road safety, increased municipal maintenance, predictive adaptive braking, and accurate routing for self-driving vehicles.

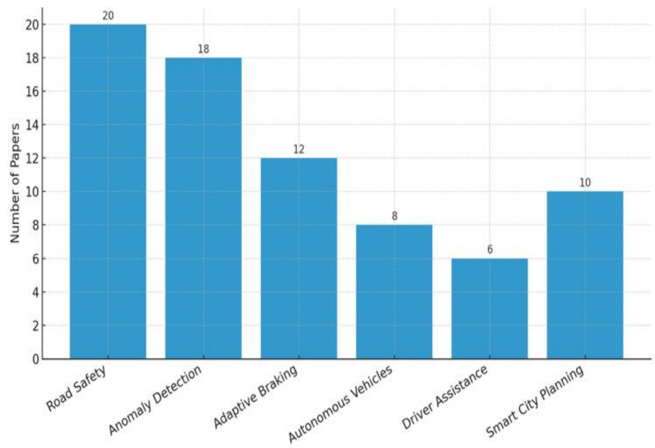

Figure 8. Research area trends reflecting use-case orientation in literature

Figure 8, also categorizes papers by these applications, indicating the relevance of speed bump detection in modern-day infrastructure. Insights obtained from the research field distribution and the societal benefit table show that the attention is on practical safety-related applications in the reviewed literature. Interest has shifted towards Speed Bump Detection and Road Condition Monitoring; the latter category reflects the change and need to improve road safety and city resource utility. These domains are certainly applicable to social oriented goals such as avoiding accidents, predictive maintenance, and better vehicle response systems. However, topics such as Autonomous Vehicle Systems, Driver Assistance, and Feature Selection/Optimization are underrepresented which could indicate opportunities to investigate unexplored regions in proactive automation and system-level intelligence. While the reviewed works contribute significantly to reactive safety and localized interventions, the lower focus on adaptive or fully autonomous systems highlights an opportunity to broaden research toward scalable, predictive, and end-to-end intelligent transport solutions. This observation underscores the need for balanced advancement across both foundational technologies and real-world implementations to maximize societal impact.

Research Trends and Study Types: Empirical studies, including practical application, as well as experimental tests, are the majority, showing the emphasis on practical application. Although there are fewer non-empirical studies, these offer helpful theories, complementing the creation of the underlying foundation of speed bump detecting technologies.

The results indicate notable advancement in speed bump detecting methods, whereby AI, together with hybrid approaches, are gaining prominence. Progress has indeed occurred, but there continue to be issues relating to generalization across data, together with adaptability, necessitating further research. The application of these innovations in real-world scenarios indicates increased contributions toward road safety, as well as toward autonomous driving systems. Figure 9, shows comparative distribution over time of non-empirical vs. empirical studies.

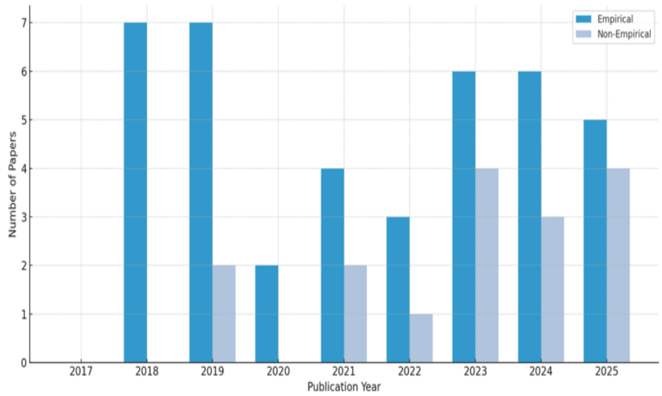

Figure 9. Empirical vs. non-empirical papers over the years

3.4 Key Techniques for speed bump detection in smart transportation system

The deployment of effective speed bump detection systems depends on the convergence of various sensing technologies, machine learning models, and embedded platforms that enable real-time environmental understanding, as given in Figure 10. As urban mobility evolves toward automation, the ability to detect, interpret, and respond to road-level anomalies such as speed bumps is essential for ensuring vehicle safety, passenger comfort, and infrastructure intelligence. This section outlines the principal technologies and methodologies that underpin modern speed bump detection systems and highlights how each contributes uniquely to the broader ecosystem of intelligent transportation.

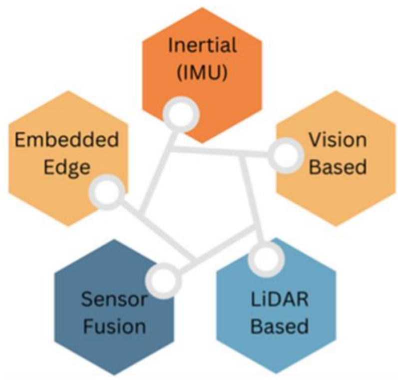

Figure 10. Classification of speed bump detection techniques

Inertial Sensing and IMU-Based Detection: One of the earliest and most commonly used approaches for speed bump detection involves the use of Inertial Measurement Units (IMUs), which typically consist of accelerometers, gyroscopes, and sometimes magnetometers. These sensors measure the acceleration and angular velocity of a vehicle along multiple axes, providing a continuous stream of motion data.

When a vehicle traverses a speed bump, it experiences a distinct pattern of vertical displacement, which generates specific signatures in the accelerometer's z-axis output, as shown in Figure 11. By analyzing features such as peak amplitude, standard deviation, jerk, energy, and root mean square (RMS) values, these patterns can be isolated and used as indicators of a speed bump event.

Key advantages of IMU-based systems include:

- Independence from lighting and visibility conditions.
- Low cost and ease of integration into smartphones or vehicle ECUs.
- Compatibility with offline and on-device processing.

Despite these benefits, inertial sensing suffers from noise sensitivity, vehicle dependency, and difficulty distinguishing between similar anomalies like potholes or speed breakers of irregular shapes. These limitations are often mitigated through feature selection, sensor fusion, or the application of classical machine learning classifiers such as Support Vector Machines (SVM), Decision Trees, or K-Nearest Neighbors (KNN).

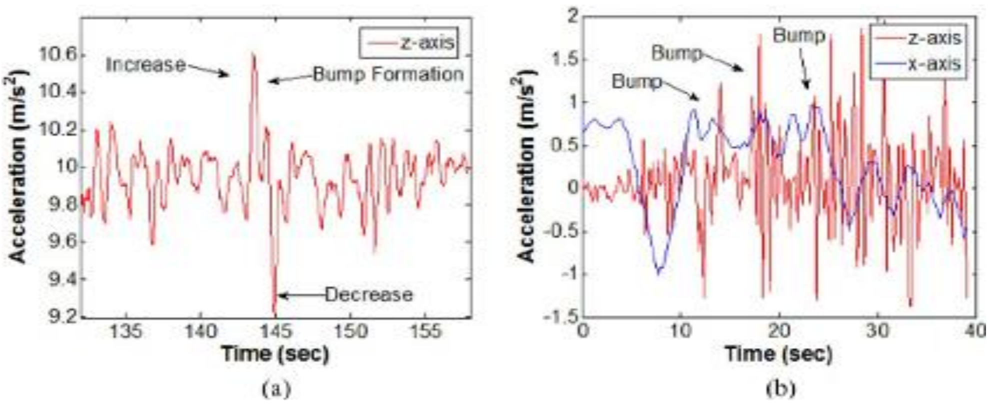

Figure 11. Sample IMU data signature while crossing a speed bump

Vision-Based Techniques and Deep Learning Models: Visual perception systems remain a cornerstone of autonomous navigation and anomaly detection. In the context of speed bump detection, camera-based systems analyze the road surface in front of the vehicle to identify characteristic shapes, colors, shadows, or textures that suggest the presence of a speed bump.

Earlier methods employed edge detection, morphological operations, and contour extraction to isolate features from grayscale or RGB images. These techniques, however, were highly sensitive to lighting changes, occlusion, and inconsistent markings, often resulting in reduced accuracy under real-world conditions.

The introduction of Convolutional Neural Networks (CNNs) and deep learning architectures significantly improved system performance. Modern models such as YOLO (You Only Look Once), SSD (Single Shot MultiBox Detector), and Faster R-CNN are capable of real-time object detection with high precision and recall. These models are trained on annotated datasets and can generalize across varying visual contexts, provided sufficient diversity in training data flow chart shown as Figure 12.

Features of vision-based models include:

- Hierarchical feature extraction from raw image data
- Real-time detection and localization
- Integration with ADAS and navigation systems

Challenges remain in the form of dataset scarcity, especially in regions like India where speed bumps are often unpainted, irregular, or partially obstructed. Additionally, computational demands may limit the applicability of these models on resource-constrained platforms unless optimized through model compression techniques.

LiDAR and 3D Surface Profiling: A steady rate of increased study over time, peaking both in contributions over the years 2021 and 2022, indicates the greater relevance of computerized road processes. Figure 3 indicates the annual distribution of papers on studies of speed bumps over the period 2017-2023. Light Detection and Ranging (LiDAR) provides high-resolution, three-dimensional mapping of the environment by emitting laser pulses and measuring their return time. In speed bump detection, LiDAR generates dense point clouds that represent road surface elevations with fine granularity, enabling the precise identification of elevation changes characteristic of speed bumps.

LiDAR-based detection is particularly beneficial in scenarios where:

- Visual cues are unreliable (e.g., nighttime, fog, occlusion)
- High-resolution terrain profiling is required
- Detection is part of a larger SLAM or autonomous mapping framework

The primary drawback is the cost and computational overhead associated with LiDAR systems. These technologies are currently limited to research platforms, high-end AVs, or smart infrastructure projects due to the expense and power requirements. Nevertheless, as LiDAR miniaturization and cost reduction continue, its role in surface anomaly detection is expected to grow.

Sensor Fusion for Multi-Modal Detection: A steady rate of increased study over time, peaking both in contributions over the years 2021 and 2022, indicates the greater relevance of computerized road processes. Figure 3 indicates the annual distribution of papers on studies of speed bumps over the period 2017-2023. The limitations of individual sensing modalities have led to the rise of sensor fusion-based detection frameworks, which combine inputs from multiple sources—typically vision systems, inertial sensors, and GPS data. Sensor fusion improves the reliability of detection and reduces false positives by correlating physical and visual signals. Flowchart shown in Figure 13.

A common architecture involves:

- Pre-processing sensor data streams for noise reduction
- Temporal synchronization of vision and IMU data
- Use of fusion algorithms (e.g., Kalman filters, Bayesian inference, attention mechanisms)
- Decision layers using ensemble machine learning models or neural networks

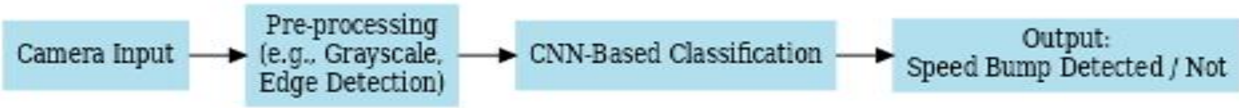

Figure 12. Vision-based detection pipeline

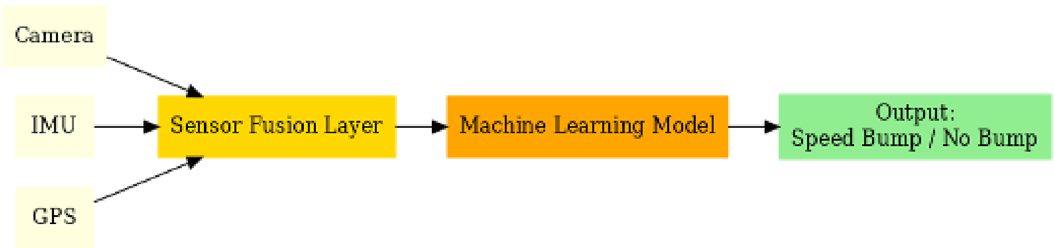

Figure 13. Sensor fusion architecture

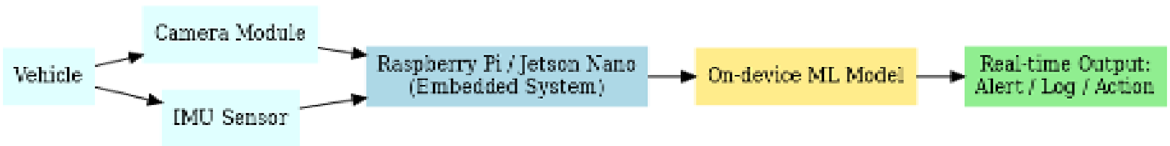

Figure 14. Embedded systems and edge ai architecture

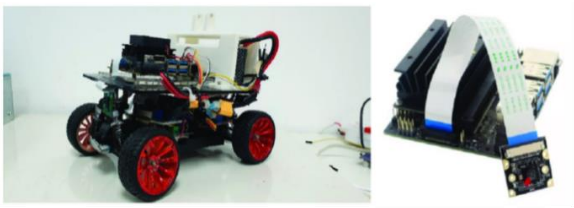

Figure 15. Prototype deployment setup on embedded system

By leveraging the complementary strengths of different sensors, fusion-based systems enhance contextual awareness and adaptability to varying road conditions. For instance, an IMU can confirm the presence of a bump detected visually, or vice versa, improving classification confidence. These systems are increasingly deployed in real-time environments and offer a scalable path to deployment in heterogeneous fleets, where hardware configurations may vary between vehicles.

Embedded Systems and Edge AI Platforms: The deployment of speed bump detection in real-world vehicles demands low-latency, resource-efficient processing, which is made possible through edge computing platforms. Devices such as Raspberry Pi 4, NVIDIA Jetson Nano, and Google Coral Dev Board are widely used to host machine learning models and sensor integration frameworks directly on vehicles. Flowchart shown in Figure 14.

These platforms support:

- On-device inference without needing cloud connectivity
- Use of TensorRT, ONNX Runtime, or PyTorch Mobile for efficient model deployment
- Real-time alerts, control signals, or logging based on detected anomalies

To meet real-time requirements, models are often compressed using quantization, pruning, or knowledge distillation techniques. The rise of TinyML further enables the execution of optimized neural networks on microcontrollers, opening doors for ultra-low-cost detection systems. Sample prototype shown in Figure 15.

Collaborative Mapping and Crowdsourced Detection: An emerging frontier in speed bump detection is the use of collaborative mapping, where data from multiple vehicles is aggregated to create and update road condition databases. This approach parallels crowdsourced mapping in navigation platforms and has the potential to scale rapidly, especially in regions where manual infrastructure updates are infrequent.

- V2X (Vehicle-to-Everything) communication for real-time data sharing
- Edge-cloud synchronization for anomaly aggregation and analysis
- Decentralized datasets that adapt based on user feedback and continuous sensor inputs, enabling self-learning detection models

4. CONCLUSION AND FUTURE SCOPE

4.1 Research agenda

Speed bumps serve an important role in controlling car speeds and highway safety. With new transportation infrastructure and emerging autonomous technology, correct speed bump detection is becoming increasingly important. In this work, a variety of techniques for speed bump detection, including computer vision, sensors, and artificial intelligence, have been examined, analyzed, and compared in terms of performance and complexity.

Despite significant progress in this area, several challenges remain. One of the biggest issues is real-world adaptability. Many detection models perform well under controlled conditions but struggle when faced with different lighting, weather, and road textures. Future research should focus on developing detection systems that can operate reliably across diverse environments.

Another challenge is diversity in datasets. Most studies use datasets collected in a specific region, and therefore, it is challenging to use such models in a worldwide scenario. Broadening datasets to cover a variety of geographical locations, types of road, and types of speed bumps will enhance accuracy in detection.

Cost and scalability cannot be disregarded, either. High-tech, sensor-based methodologies can function beautifully, but rolling them out at a widespread level, and even in developing nations, is not yet an option. Investigators will have to go in search of low-cost and scalable platforms for detection, balancing cost and performance, with access for all in mind.

<u>To continue enhancing speed bump detection, future work will have to explore:</u>

- Improved AI models with fewer processing requirements but high accuracy.
- Combining several such technologies such as GPS, accelerometers, and computer vision in one system for a robust detection system Developing smart highway infrastructure, through which automobiles can speak with highways for added efficiency and security.
- Expanding public datasets for model training with a greater diversity of types of roads and improving overall performance.
- Improving vehicle response features, such as adaptive braking and suspension levels, for a smoother ride.

4.2 Conclusion

The study reviewed several speed bump detection methods and their implementation in modern transport systems. While vision-based, sensor-based, and AI-driven models have improved the detection, real-time responsiveness, dataset problems, and costs remain significant obstacles to widespread implementation.

Our findings demonstrate that hybrid approaches—that combine computer vision, sensors, and artificial intelligence—are most promising for speed bump detection with high accuracy. However, to enable the implementation of such solutions in real-world settings more effectively, there is a need for continued research and development. Future research should try to enhance detection accuracy, enlarge datasets, and integrate detection models into intelligent transportation systems.

Moving forward, researchers and engineers must work together to develop practical, scalable, and economically feasible solutions to enhance road safety. The intersection of real-time vehicle response systems, IoT, and AI will form a key part of defining future speed bump detection. As development takes form, smarter roads, safer cars, and optimized transportation networks will become a godsend for drivers, urban planners, and walkers alike.

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