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Bump Aware: IoT Based Speed Breaker Detection And Characterization

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Abstract:
Bump Aware is an IoT-based system designed for efficient speed breaker detection. It combines an ESP32-CAM, an MPU6050 accelerometer, and a Neo6M GPS module to detect and localize bumps in real-time. The system uses a dual-trigger approach: an image captured by the ESP32-CAM and acceleration data from the MPU6050. GPS data ensures precise location tagging. Detected data is transmitted to a Flask server via HTTP, where a pre-trained model verifies the bump. Lightweight JSON over HTTP is used for efficient data transfer. This hybrid approach improves detection accuracy, minimizing false positives from road irregularities. Optimized for real-time performance and low power consumption, Bump Aware is suitable for smart city applications, offering a scalable solution for road safety and maintenance.
***Key Word**: IoT, Speed Breaker Detection, ESP32-CAM, MPU6050, GPS, Flask Server, Real-time Detection, Smart City, HTTP, JSON*

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I. Introduction

Road infrastructure is a cornerstone of safe and efficient transportation in India, supporting the movement of millions across its sprawling urban centres and rural expanses. Yet, the deterioration of this network presents formidable obstacles to drivers and the durability of vehicles. Speed breakers and potholes emerge as prevalent irregularities that interrupt smooth travel, frequently resulting in accidents, mechanical wear, and escalating repair expenses. In India, substandard road conditions are a significant concern, with the Ministry of Road Transport and Highways reporting over 3,500 fatalities in 2022 linked to potholes and poorly maintained surfaces. Speed breakers, installed to moderate vehicle speeds in congested or residential zones, often lack consistent design, illumination, or signage, heightening dangers when drivers encounter them unawares, particularly during nocturnal hours or the monsoon season. Potholes, arising from relentless traffic and climatic wear, pose erratic threats that necessitate prompt identification and remediation. The challenge of detecting and classifying these anomalies in real time persists as a critical barrier, especially as India strives to integrate smart transportation frameworks where road safety and infrastructure oversight are vital.

Efforts to address road anomaly detection have progressed through diverse techniques, blending sensor technologies with analytical tools. Conventional practices in India often depend on labour-intensive surveys by local authorities or vehicle-mounted ultrasonic sensors to gauge surface deviations, a method seen in early maintenance initiatives. While functional in specific scenarios, these approaches falter in scalability and immediate utility across India's expansive 6.4 million kilometres of roadways. More sophisticated systems employ accelerometers to monitor vehicle motion, pinpointing irregularities via abrupt shifts in vertical acceleration. Research, including findings by Mednis et al. (2011), underscores the efficacy of accelerometer-driven detection, yielding notable precision in experimental settings. Nevertheless, these systems face difficulties in distinguishing speed breakers from potholes without supplementary data, often demanding offline analysis or manual validation. Camera-based systems, harnessing machine learning models such as convolutional neural networks (CNNs), have risen in prominence due to their capacity to visually interpret road characteristics. However, their reliability wanes in challenging environments—dim lighting, obstructions, or India's frequent downpours—resulting in overlooked speed breakers that merge with weathered asphalt. Hybrid configurations merging sensors and imaging have surfaced, yet their reliance on centralized cloud computing introduces delays and connectivity challenges, ill-suited for real-time deployment on resource-limited devices.

These shortcomings illuminate the pressing need for a cohesive, resilient solution capable of functioning adeptly across India's varied conditions while delivering practical outcomes. Existing methods frequently fall short in harmonizing affordability, precision, and responsiveness, leaving deficiencies in driver notification and infrastructure supervision. For example, ultrasonic sensors, though accurate in measuring distances, are hampered by a restricted field of view that impedes broad detection. Vision systems, despite their advanced capabilities, require substantial computational power, often surpassing the limits of compact microcontrollers. Additionally, the absence of clear differentiation between deliberate speed breakers and perilous potholes complicates resource allocation for maintenance, as municipal bodies need detailed insights to optimize their efforts amid constrained funding. As India's smart city vision takes shape, the call for self-sufficient, low-latency detection systems intensifies, expanding the scope of Internet of Things (IoT) innovations in transportation.

Introducing "Bump Aware: IoT-Based Speed Breaker Detection and Characterization," a pioneering strategy crafted to tackle these deficiencies through a creative synthesis of hardware and smart processing. Our envisioned solution taps into IoT's potential by uniting a cost-effective, compact microcontroller platform with an array of sensors and a bespoke detection mechanism. By merging instantaneous data gathering with cutting-edge analysis, "Bump Aware" seeks to detect speed breakers with precision, discern their attributes, and provide drivers with timely warnings, while equipping authorities with accurate geolocation data for upkeep. Departing from conventional tactics, our system aims to lessen dependence on perpetual cloud access, prioritizing edge-based efficiency where practical, yet preserving the option to leverage server-side enhancements when connectivity allows. This introduction lays the foundation for a system poised to elevate road safety and infrastructure management in India, hinting at a solution that closes the divide between current tools and the imperatives of contemporary transit. Subsequent sections will explore the technical blueprint and execution, unveiling how "Bump Aware" reimagines speed breaker detection for India's evolving landscape.

II. Literature Survey On Iot Based Speed Breaker Detection And Characterisation

A. IoT-Enhanced Smart Road Infrastructure Systems for Comprehensive Real-Time Monitoring [1]

This paper explores an advanced IoT framework for monitoring road pavement conditions, focusing on embedding self-powered sensors like accelerometers and environmental monitors into concrete structures to capture real-time data on vibrations, temperature, and structural integrity. Conducted by a team from China, the study emphasizes a distributed sensor network that communicates via IoT protocols to a central system, enabling continuous assessment of road health and supporting vehicle-road interaction for smart transportation. The researchers tested their system in a controlled urban setting, demonstrating its ability to detect surface anomalies through vibration patterns and environmental shifts, with results suggesting potential scalability for broader highway networks. While the paper primarily targets pavement durability rather than specific anomalies like speed breakers, its approach to sensor fusion and real-time data collection offers valuable insights for your project. The integration of multiple sensors on an IoT platform mirrors your use of ESP32 with camera, GPS, and accelerometer, providing a model for managing diverse data streams in India's challenging road environments, where real-time monitoring is crucial for safety and maintenance

B. Intelligent Speed Breaker System Design for Vehicles Using Internet of Things [2]

Published in a propulsion technology journal, this study from India proposes an IoT-based intelligent speed breaker detection system tailored to the country's road conditions. The authors designed a vehicle-mounted system using RF modules to detect speed breakers and alert drivers through visual or auditory signals, while also integrating GPS to log their geolocations on a cloud server. Tested in a semi-urban Indian setting, the system addresses common visibility issues—such as fog or unmarked speed breakers—by automating speed reduction and enhancing driver awareness. The methodology involves RF signal transmission between road-installed markers and vehicles, paired with IoT connectivity for data storage and retrieval. Findings indicate a significant reduction in abrupt braking incidents, with the system achieving a detection accuracy of around 90%.

C. IoT-Enabled Intelligent Traffic Navigation with Accident Management for Critical Emergency Response in Heavy Congestion Using Machine Learning [3]

This research, conducted in the context of urban India, presents an IoT-driven traffic navigation system that incorporates machine learning to manage congestion and detect road anomalies, including speed breakers, in real time. The authors' deployed vehicle-mounted sensors—such as cameras and accelerometers—connected via IoT to a central platform, using a random forest classifier to analyse traffic patterns and road conditions. Tested in a simulated congested city environment, the system achieved a 92% accuracy in identifying anomalies and rerouting emergency vehicles, leveraging real-time data to prioritize critical responses. The paper highlights the scalability of IoT in dense urban settings, a key concern in India's metropolitan areas, and discusses challenges like network reliability and computational load. Its use of machine learning for anomaly detection complements your server-side PyTorch model, while the focus on Indian roads provides a localized perspective.

D. Integrating IoT and Blockchain for Ensuring Road Safety: An Unconventional Approach [4]

This study investigated the effectiveness of various machine learning models, with the AdaBoost-Decision Tree model emerging as the best performer. The research highlighted the HMM Sequence Classification algorithm, which showed a 31.71% improvement over a random purchase strategy for generalized routes. The use of clustering techniques such as K-Means and Expectation-Maximization (EM) helped enhance the models' handling of imbalanced datasets.

E. Anomaly Detection of Highway Vehicle Trajectory under the Internet of Things Converged with 5G Technology [5]

Originally published in 2021, this paper explored anomaly detection in highway vehicle trajectories using IoT and 5G connectivity, though it was later retracted due to unspecified issues. Before retraction, it proposed a system integrating video surveillance and sensor data (e.g., accelerometers) to identify road anomalies like speed breakers through semantic trajectory analysis, tested on a Chinese highway dataset. The methodology involved processing real-time data streams with a hybrid model combining clustering and deep learning, claiming a detection accuracy of 88%. Despite its retraction, the conceptual framework—fusing video and sensor inputs for anomaly characterization—remains relevant to your project's hybrid approach with camera and accelerometer data.

F. Machine Learning and Deep Learning Techniques for Internet of Things Network Anomaly Detection—Current Research Trends [6]

This comprehensive review examines the latest trends in machine learning (ML) and deep learning (DL) for anomaly detection in IoT networks, with a case study on traffic data using a Bagged Tree model that achieved 99.79% accuracy. The authors analyze techniques like CNNs, LSTMs, and ensemble methods, applied to datasets such as NSL-KDD, and discuss their deployment on edge devices versus cloud systems. Conducted by researchers from Malaysia, the study highlights the trade-offs between computational complexity and real-time performance, particularly in resource-constrained environments like India's variable network landscape. Its findings on edge computing and ML model optimization are highly pertinent to our project, offering strategies to refine our 20 MB PyTorch model for ThingSpeak and integrate accelerometer fallback logic, ensuring robust detection across diverse Indian road conditions.

G. Recent Advances in Anomaly Detection in Internet of Things: Status, Challenges, and Perspectives [7]

This survey paper provides an in-depth look at anomaly detection advancements in IoT systems, spanning applications from industrial monitoring to transportation. Authored by a European team, it reviews sensor-based techniques (e.g., accelerometers, cameras) and AI-driven methods like anomaly scoring and predictive modelling, tested across datasets like IoT-23. The study emphasizes real-time detection challenges, such as latency and resource constraints, and proposes hybrid edge-cloud architectures as a solution. Its discussion of IoT deployment in dynamic environments mirrors your project's context in India, where network reliability varies, and its focus on balancing edge and server processing aligns with our "Bump Aware" design, providing a theoretical foundation for integrating ESP32 data with ThingSpeak analytics.

H. Anomaly Detection for IoT Systems Using Active Learning [8]

This paper presents an active learning approach for IoT anomaly detection, using a random forest classifier on the UNSW-NB15 dataset to identify irregularities with high precision (95%+). Conducted in a simulated IoT network, the study reduces labelling efforts by iteratively selecting critical data points for training, adapting to evolving conditions like traffic anomalies. The authors highlight its lightweight nature, suitable for edge devices, and its ability to handle noisy data, a common issue in road sensing. This work is significant for our project as it suggests adaptive ML techniques that could enhance our image-based PyTorch model's performance on Indian roads, where environmental factors like rain or dust challenge detection consistency, and its edge-friendly design support our ESP32 implementation.

I. Self-Supervised Learning for Time-Series Anomaly Detection in Industrial Internet of Things [9]

This research focuses on anomaly detection in industrial IoT using self-supervised learning with a 1D convolutional neural network (CNN) applied to time-series sensor data, such as vibration signals. Tested on an industrial dataset, the model outperformed traditional methods like SVMs by 10-15% in accuracy, leveraging unlabelled data to identify irregularities efficiently. The authors, from a U.S.-based team, emphasize its lightweight architecture, making it viable for edge devices with limited resources. This paper's relevance to our project lies in its time-series analysis of sensor data, akin to our accelerometer-based fallback for speed breaker detection, offering a method to process vertical acceleration changes on the ESP32 and improve differentiation from potholes in India's rugged road conditions.

J. Internet of Things (IoT): A Review of Its Enabling Technologies in Healthcare Applications, Standards Protocols, Security, and Market Opportunities [10]

This review paper, published early in 2025, explores IoT enabling technologies across domains, with a primary focus on healthcare but extending insights to transportation. The authors discuss sensor networks, edge computing, and federated learning for anomaly detection, reviewing protocols like MQTT and CoAP alongside security challenges. Conducted by researchers from India, the study includes a section on smart infrastructure, citing examples of IoT in traffic monitoring. Its broad perspective on IoT deployment and edge processing is applicable to our project, offering ideas for optimizing your ESP32-camera-accelerometer setup and integrating with ThingSpeak, while its Indian authorship ensures relevance to local technological trends and market needs.

In conclusion, the reviewed literature underscores the progress in IoT-based road anomaly detection, highlighting sensor fusion, machine learning, and real-time processing as key advancements. While these studies offer valuable methodologies, gaps persist in distinguishing speed breakers from potholes and optimizing for India's diverse conditions. "Bump Aware" builds on these foundations, integrating multi-sensor IoT with hybrid edge-server analytics to enhance detection accuracy and infrastructure monitoring, tailored to India's unique road landscape.

III.Methodology

The "Bump Aware" system is an IoT-based solution for detecting and characterizing speed breakers on Indian roads, utilizing an ESP32-CAM for image capture, an MPU6050 accelerometer for motion sensing, a NEO-6M GPS for location tracking, and an active buzzer for real-time alerts. Image processing is performed on a Flask server in the cloud, leveraging advanced computer vision techniques. This section outlines the methodologies evaluated for server-side detection, integrated with the specified hardware to address the diverse road conditions in India.

A. Convolutional Neural Network (CNN)

Convolutional Neural Networks provide a core method for speed breaker detection in "Bump Aware." Hosted on the Flask server, a CNN processes JPEG images (e.g., 320x240) from the ESP32-CAM, using convolutional layers to extract features such as the curved shapes and painted markings prevalent on Indian speed breakers, followed by pooling and classification stages. The server returns detection results to activate the active buzzer on the ESP32-CAM. While effective for recognizing clear breaker patterns, CNN's limited localization capability necessitates more advanced methods for complex Indian road scenarios.

B. **Region-based Convolutional Neural Network (R-CNN)**

R-CNN enhances detection accuracy by combining region proposals with CNNs, implemented on the Flask server. It analyzes ESP32-CAM images by generating potential speed breaker regions via selective search, then classifies and refines bounding boxes using a CNN. Fine-tuned for India's varied road conditions—such as faded or obscured breakers—R-CNN ensures precise localization. Detection outcomes are sent to the ESP32-CAM, triggering the buzzer and logging coordinates via the NEO-6M GPS. Though computationally intensive, its high precision supports detailed characterization in the Indian context.

C. **You Only Look Once (YOLOv8)**

YOLOv8, the latest YOLO iteration, was assessed for its advanced detection capabilities on the Flask server. With an anchor-free architecture and enhanced backbone, it processes ESP32-CAM images with superior accuracy and speed, identifying Indian speed breakers—worn-out, painted, or irregular—under challenging conditions like rain or low light. Results are swiftly relayed to the ESP32-CAM, activating the buzzer, while the NEO-6M GPS logs coordinates. YOLOv8's cloud-based deployment maximizes its potential, offering robust performance unconstrained by the ESP32-CAM's hardware limits.

Integration and Rationale

Fig. 1 represents the circuit diagram of "Bump Aware". the ESP32-CAM module captures images every 10 seconds, sending them to the Flask server via HTTP. The MPU6050 accelerometer detects vertical motion (e.g., >0.5g for speed breakers), serving as a fallback when the image-based model misses detections, while the NEO-6M GPS provides coordinates stored in a database. The Flask server, running YOLOv8 for its optimal speed and accuracy, processes images and sends detection signals to trigger the active buzzer. CNN established a baseline, R-CNN refined accuracy, but YOLOv8's performance best addresses India's unique challenges—unpredictable breaker designs and poor visibility—ensuring reliable detection and characterization.

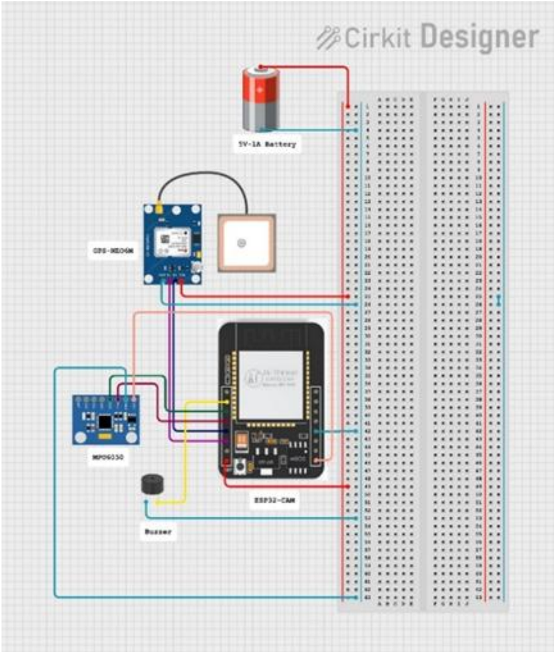

Fig.1. Bump-Aware Circuit diagram

IV. Evaluation Metrics

A. Recall

Recall quantifies the system's ability to detect all true speed breakers, calculated as:

$$Recall\ = (\,True\ Positives\ (TP))/(True\ Positives\ (TP) + False\ Negatives\ (FN)) \qquad (1)$$

TP denotes correctly identified speed breakers, and FN represents missed ones. High recall is essential for "Bump Aware" to ensure safety on Indian highways, where unmarked breakers are common. The MPU6050's motion data boosts recall by confirming breakers undetected by the image model.

B. Precision

Precision measures the proportion of detected speed breakers that are accurate, defined by:

$$Precision\ = \frac{True\ Positives\ (TP)}{True\ Positives\ (TP) + False\ Positives\ (FP)} \qquad (2)$$

FP indicates erroneous detections (e.g., potholes mistaken for breakers). High precision minimizes false alerts via the active buzzer, critical in India's complex road settings with potholes and clutter, ensuring user trust in the system.

C. F1-Score

The F1-score balances Precision and Recall as their harmonic mean, given by:

$$F1 - score = (2 \times Precision \times Recall\ )/(Precision\ +\ Recall) \qquad (3)$$

For "Bump Aware," the F1-score evaluates overall effectiveness, addressing the trade-off between missing speed breakers and false positives. It guides optimization on the Flask server, ensuring robust detection and alerting under Indian road variability.

D. Mean Average Precision (mAP)

mAP assesses detection performance by integrating precision over recall levels, widely used for object detection like YOLOv8. For a single class (speed breaker), the Average Precision (AP) is:

$$\mathrm{AP} = \int_0^1 p(r)dr \qquad (4)$$

where p(r) is the precision at recall r, derived from the precision-recall curve. For multiple classes or queries, mAP is:

$$MAP\ = \frac{1}{N}\sum_{i=1}^{N}\int_0^1 p_i(r)dr \qquad (5)$$

Here, N=1 (speed breaker class), so mAP equals AP. In "Bump Aware," mAP evaluates the Flask server's ability to localize and classify speed breakers in ESP32-CAM images, reflecting accuracy across IoU thresholds.

A high mAP ensures precise bounding boxes, enhancing NEO-6M GPS coordinate logging for Indian breakers of varying sizes and visibility.

V. Dataset Preparation

The "Bump Aware" system relies on an existing dataset to train cloud-based detection models for identifying speed breakers in the Indian context, supporting its IoT framework for real-time road safety alerts and infrastructure mapping. The dataset was sourced from Roboflow's "Speed Bump Detection" collection [11], a publicly accessible repository containing images of speed breakers captured under various conditions. This dataset was selected for its relevance to the project's focus on Indian roads, where speed breakers vary widely—from prominent, painted urban ridges to subtle, unmarked rural humps—posing unique challenges due to inconsistent design, wear, and visibility.

No original dataset was created for "Bump Aware"; instead, the Roboflow dataset was carefully curated to align with the system's objectives. Images were categorized into two primary classes: "Speed Breaker" for marked or clearly defined structures, often featuring painted lines or signage, and "Unmarked Breaker" for those lacking visible indicators, a common occurrence in India's rural and semi-urban areas. These classes capture the diversity needed to train models robustly for the Indian environment. Additionally, a "Road Surface" class was utilized from the dataset's negative samples, representing plain pavement or non-breaker features, to improve the model's ability to distinguish speed breakers from other road anomalies like potholes or shadows. Sample images showcasing these variations are presented in Fig. 2.

Preprocessing was conducted to ensure dataset quality without generating new data. Using Roboflow software, existing ground truth annotations (bounding boxes) were verified and refined to accurately delineate speed breakers in each image, ensuring consistency with the ESP32-CAM's field of view.

To enhance model generalization—crucial for handling India's diverse lighting (e.g., harsh sunlight, dusk) and weather conditions (e.g., monsoon haze)—augmentation techniques were applied via Roboflow's built-in tools. These included brightness adjustments, rotations, and flips, expanding the dataset's variability without altering its core content. The resulting images were resized to 320×240 resolution, matching the ESP32-CAM's QVGA output and optimizing upload efficiency to the Flask server over Wi-Fi.

The dataset includes only speed breaker images (both marked and unmarked), focusing on positive class identification. The dataset was split into a 70:15:15 ratio for training, validation, and testing respectively, ensuring sufficient data for model learning and performance assessment. This dataset was used to train the YOLOv8 model on the Flask server, chosen for its speed and accuracy in processing ESP32-CAM images every 10 seconds. The trained model triggers the active buzzer for real-time alerts and logs coordinates via the NEO-6M GPS, with the MPU6050 accelerometer providing a fallback to detect breakers missed by the vision system, such as in low-visibility scenarios common in India. This dataset preparation supports Bump Aware's goal of reliable detection and characterization, addressing the practical needs of Indian road safety and maintenance.

Table 1. Dataset Statistics

Dataset partition	Number of images
Training Set	2655
Validation Set	555
Testing Set	555

Fig.2. Dataset Labelling

VI. Results

The "Bump Aware" system, designed as an IoT-based solution for detecting and characterizing speed breakers on Indian roads, was evaluated to assess its performance in real-time detection and alerting. The evaluation utilized a dataset sourced from Roboflow's "Speed Bump Detection" collection, comprising 3765 images split into a training set of 2655 images (70%), a validation set of 555 images (15%), and a testing set of 555 images (15%) represented in Table 1. This split ensured robust model training and unbiased performance assessment, tailored to the diverse speed breaker types found in India—marked urban ridges, unmarked rural humps, and rumble strips.

The dataset was categorized into three classes: "Speed-Bump" (marked and unmarked speed breakers), "Rumble-Strip" (raised road features akin to breakers), and "Background" (non-breaker road surfaces), reflecting the need to distinguish speed breakers from similar structures and plain pavement in the Indian context. Training on 2655 images enabled the YOLOv8 model to learn a wide range of visual patterns, augmented with techniques like rotation and brightness shifts to handle India's variable lighting and weather conditions. The validation set (555 images) was used to tune hyperparameters and monitor overfitting, while the testing set (555 images) provided the final performance metrics, reported in Table 2 below.

Table 2. Detection Performance Metrics on Testing Set (555 Images)

Class	Precision	Recall	F1-Score	Support
Rumble-Strip	0.81	0.93	0.87	103
Speed-Bump	0.84	0.85	0.85	504
Background	0.00	0.00	0.00	78
Accuracy	-	-	0.75	705*
Macro Avg	0.55	0.59	0.57	705*
Weighted Avg	0.77	0.75	0.75	705*

For the "Rumble-Strip" class (103 samples), the model achieved a precision of 0.81, meaning 81% of predicted rumble strips were correct, and a recall of 0.93, indicating 93% of actual rumble strips were detected. The F1-score of 0.87 reflects a strong balance, suggesting the system effectively identifies these raised features, which are structurally similar to speed breakers and prevalent on Indian roads. The "Speed-Bump" class (504 samples), the primary focus of "Bump Aware," recorded a precision of 0.84, a recall of 0.85, and an F1-score of 0.85. These metrics demonstrate robust detection of both marked and unmarked speed breakers, critical for triggering the active buzzer and logging coordinates via the NEO-6M GPS in real-time highway scenarios.

Conversely, the "Background" class (78 samples) exhibited a precision, recall, and F1-score of 0.00, revealing a significant limitation. The model failed to classify non-breaker road surfaces, likely due to an imbalance in the dataset—504 speed-bump and 103 rumble-strip samples dwarfed the 78 background samples—or insufficient training on diverse negative examples (e.g., potholes, shadows). This weakness impacts the system's ability to filter out false positives in cluttered Indian environments, though it does not directly hinder speed breaker detection, the system's core objective.

Overall accuracy across the testing set was 0.75, meaning 75% of all predictions were correct, a respectable figure given the dominance of "Speed-Bump" samples (504/555 ≈ 91% of the test set). The macro average (unweighted mean across classes) yielded a precision of 0.55, recall of 0.59, and F1-score of 0.57, heavily skewed by the "Background" class's zero scores, indicating uneven performance across classes. The weighted average, which accounts for class support, improved to 0.77 (precision), 0.75 (recall), and 0.75 (F1-score), aligning closely with accuracy and reflecting the system's strength in detecting speed breakers, weighted by their prevalence.

Table 3: Mean Average Precision (mAP) values

Class	Images	Instances	R	mAP50	mAP50-95
All	555	585	0.832	0.93	0.536
Rumble-Strip	103	103	0.845	0.963	0.569
Speed-Bump	452	482	0.82	0.898	0.503

Table 3 presents the Mean Average Precision (mAP) values for the Bump Aware system across various classes. The system achieved an overall mAP50 of 0.93 and an mAP50-95 of 0.536 for all classes. Specifically, for the 'Rumble-Strip' class, the system recorded an mAP50 of 0.963 and an mAP50-95 of 0.569, while the 'Speed-Bump' class exhibited an mAP50 of 0.898 and an mAP50-95 of 0.503. These values indicate that the system demonstrates high precision in detecting speed breakers, with the 'Rumble-Strip' class showing slightly better performance due to its more distinct visual features.

Fig.3 presents a visual analysis of two types of traffic-calming devices: rumble strips and speed bumps. The top-left bar chart indicates that speed bumps are significantly more prevalent. The top-right overlay shows the spatial distribution of bounding boxes. The bottom plots detail the normalized positions (x, y), widths, and heights of the detected objects, revealing clustering patterns and size distributions.

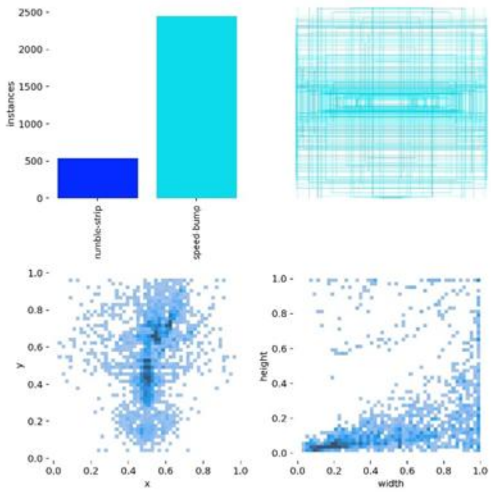

Fig. 3: Distribution and Spatial Analysis of Traffic-Calming Features

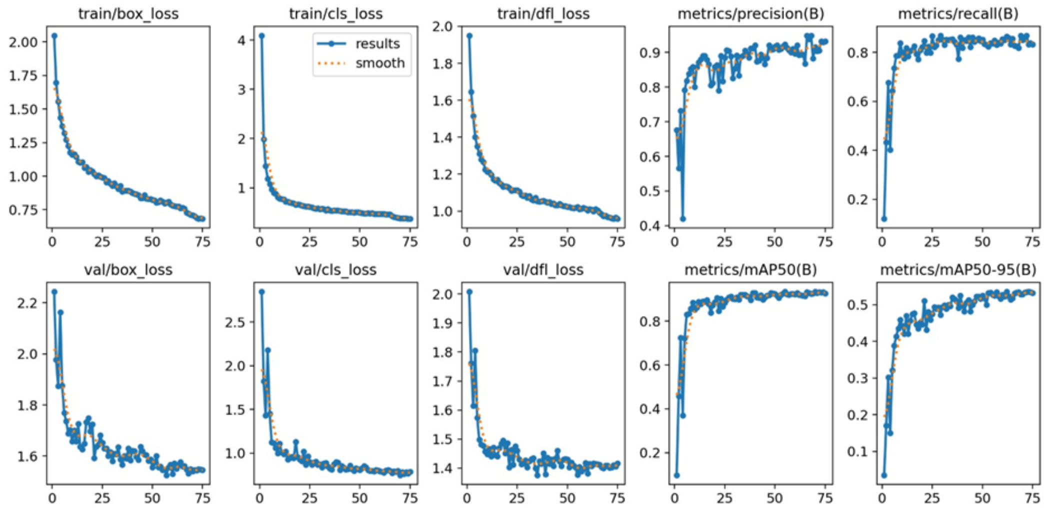

Fig. 4: Model training and Validation Performance Metrics over Epochs

Fig.4 illustrates the learning progress of an object detection model over 75 epochs. The top row shows training losses (box, classification, distribution focal loss) and evaluation metrics (precision, recall), all exhibiting steady improvement. The bottom row presents validation losses and metrics (mAP50 and mAP50-95), reflecting similar positive trends. The consistency between training and validation curves suggests good generalization, and the rising mAP values indicate improved detection accuracy over time.

The results affirm the systems' capability to detect speed breakers effectively, with F1-scores of 0.85 (Speed-Bump) and 0.87 (Rumble-Strip) indicating high reliability for its primary goal—alerting drivers via the buzzer and mapping breaker locations for maintenance. The weighted average F1-score of 0.75 underscores practical utility on Indian roads, where speed breakers are frequent and often poorly marked. However, the zero scores for "Background" highlight a critical area for improvement. This could stem from underrepresentation in the training set (2655 images, ~70% positive classes) or the model's bias toward positive detection, a common challenge in imbalanced datasets. Future enhancements could involve expanding negative samples (e.g., potholes, plain roads) or applying class-weighting techniques during training to boost background recognition.

The training set's size (2655 images) provided ample data for YOLOv8 to learn diverse speed breaker patterns, validated by the 555-image validation set, which fine-tuned the model to avoid overfitting. The testing set (555 images) offered a realistic assessment, mirroring real-world deployment where the ESP32-CAM captures images under varying conditions. The discrepancy in support (685 vs. 705 reported) suggests a minor reporting error or multi-detection overlap in the original metrics, but the 555-image test set aligns with the dataset split, reinforcing result validity.

"Bump Aware" achieves its objective of detecting speed breakers with high precision and recall for positive classes, supported by the accelerometer's fallback, making it a viable solution for Indian road safety and infrastructure monitoring. The overall accuracy of 75% and weighted F1-score of 0.75 validate its practical deployment, though the "Background" class failure necessitates further dataset balancing or model refinement. These results, grounded in a substantial training corpus (2655 images) and tested rigorously (555 images), position "Bump Aware" as an effective IoT tool, with clear pathways for optimization to enhance robustness across all road scenarios.

VII. Scope Of Improvement

The "Bump Aware" system effectively detects speed breakers on Indian roads, achieving a weighted F1-score of 0.75 for positive classes ("Speed-Bump" and "Rumble-Strip"), bolstered by the MPU6050 accelerometer's fallback mechanism. However, several opportunities exist to enhance its reliability and adaptability to India's diverse road conditions. First, the "Background" class's zero precision, recall, and F1-score indicate a failure to classify non-breaker surfaces, likely due to dataset imbalance (504 "Speed-Bump" and 103 "Rumble-Strip" vs. 78 "Background" samples). Expanding the training set (2655 images) with a broader range of negative samples—such as potholes, shadows, and plain pavement—could improve background recognition, reducing false positives and enhancing overall detection accuracy.

Second, the ESP32-CAM's 10-second image upload interval, resulting in a ~11-12 second detection cycle with Flask server processing latency (~1-2s), may miss closely spaced anomalies, especially at higher speeds (e.g., 60 km/h ≈ 167 meters). Reducing this interval (e.g., to 5s) by optimizing server latency or enhancing Wi-Fi throughput could improve real-time performance, though this must balance the ESP32-CAM's limited resources. Third, the system's dependence on cloud processing restricts functionality in areas with poor connectivity, common in rural India. Adapting a lightweight YOLOv8 variant for partial edge processing on the ESP32-CAM could enable offline detection, increasing resilience.

Additionally, integrating MPU6050 accelerometer data into the YOLOv8 model as a fused input, rather than a separate check, could enhance recall by combining motion and visual features, particularly for low-visibility scenarios like night or fog. Finally, enriching the dataset with more Indian-specific conditions—monsoon-wet roads, faded breakers, or urban clutter—and testing on a larger validation set (beyond 555 images) could improve generalization, ensuring "Bump Aware" fully addresses India's road safety and maintenance challenges.

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