RESEARCH PAPER

EDGE-OPTIMIZED TINYML FRAMEWORK FOR REAL-TIME MULTI-CLASS ROAD SURFACE FAULT DETECTION IN IOT ENVIRONMENTS

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ABSTRACT

There are potholes, cracks and uneven parts of roads which cause serious safety risks, escalate maintenance of vehicles and make maintenance of infrastructure a huge challenge. Conventional approaches to road condition monitoring, such as manual inspection or cloud-based analytics, are usually labor-intensive, expensive, and cannot be used to provide real-time monitoring. In this paper, an edge-efficient TinyML framework to detect road surface faults in multi-classes in IoT settings is presented. The suggested system combines a lightweight, quantized neural network that can be able to classify several types of faults on-device with a small latency and energy consumption. The robust detection even in changing conditions of the roads is achieved through sensor fusion of camera and vibration data which are used by the framework. Edge inference enables lower reliance on the high-bandwidth connectivity through sending only alert and metadata to a centralized IoT platform to be visualized and long-term monitored. Experimental results of a dataset of city and urban semi-urban roads contribute to the overall classification accuracy of 93.6, real-time inference of 28 frames per second and energy consumption of less than 2 W. The TinyML optimization and multi-class fault detecting, combined with the IoT inclusion in the framework makes the smart city road monitoring scalable and energy-effective, able to plan performance on proactive maintenance and improve road safety as well as monitor infrastructure conditions continuously in an automated manner.

Keywords: TinyML, Road Surface Fault Detection, Edge Computing, IoT, Real-Time Monitoring, Potholes, Cracks, Smart City.

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I. INTRODUCTION

Potholes, cracks and irregular pavements are some of the road surface defects that are a serious safety hazard to vehicles, they raise maintenance costs and undermine transportation efficiency [1]. These defects are essential in ensuring that road maintenance and management of smart city infrastructure is detected and acted upon before they occur. Old methods such as walking inspections and car surveys are labor intensive, time consuming, and prone to human mistakes, and thus do not suit continuous monitoring [2], [4]. The latest developments in computer vision and deep learning have made it possible to detect defects on the road surface automatically. Picture-based techniques using convolutional neural networks (CNNs) and object recognition neural networks like YOLO have demonstrated great potential in detecting and categorizing road defects on pixel-level basis [2], [4]. Nevertheless, these techniques tend to be sensitive to environmental situations such as light variations, weather patterns and occlusions that can severely impair detection performance [1], [4]. To overcome these shortcomings, scientists have come up with non-image based sensors, including LiDAR and laser scanners to provide depth data and enhance resilience in adverse conditions [1]. Moreover, edge computing and federated learning have become the new paradigm that could be used to achieve real-time and privacy-aware road monitoring. On-device inference can be done with edge-based processing to minimize latency and reliance on high-bandwidth connectivity, whereas federated learning can be used to train a model simultaneously on multiple vehicles without exchanging unprocessed data [5]. Recent research also emphasizes the significance of post-processing methods, including bounding box refinement, to improve the accuracy of detection of the conventional deep neural network results [3]. Although these developments have been made, most current systems either are cloud-computer reliant or concentrate on the detection of a single class, which restricts their ability to scale and be applicable in real-time in IoT settings. This leads to the requirement of a lightweight, edge-selected TinyML approach that can identify and distinguish between multi-class road surface faults using minimal energy use and minimal latency, which can offer an efficient and realistic solution to smart city road infrastructure management.

II. Related Works

The recent studies in the area of road surface defect detection progressively employed the use of machine learning, deep learning, and edge computing technologies to obtain real-time, automated monitoring. G. G. A YOLOv7 pothole detection system proposed by R. and R. G. P. [6] running on a Raspberry Pi edge computer was shown to be close to real time and use low energy levels, making it scalable to high deployment. They took a more pragmatic approach to emphasize the practical utility of combining machine learning with inexpensive hardware, but they mainly concentrated on potholes of one class. Subbiah et al. [7] carried on with this idea by adding to it object detection via YOLOv8 and pothole monitoring through IoT. Their framework used high-resolution data along with CNN-based bounding box prediction to provide a visual highlight of potholes to navigate safely and implement autonomous cars. This paper strengthened the usefulness of lightweight CNN models in edge based road surveillance, albeit with little multi-class defect detection. The use of attention and sophisticated network structures have as well demonstrated potential in augmenting detection robustness and accuracy. In their article, Li et al. [8] presented a road defect detector network, named CSENet, which makes use of the context channel spatial attention, multi-scale convolution heads, and multi-semantic space modules. CSENet exhibited better mean average precision (mAP) and F1 scores than YOLOv8s, solving the issue of environmental interference, small-scale defects, and global feature aggregation. In a similar manner, Xiong et al. [9] developed MSLR-YOLO which is a lightweight multi-scale attention network and is edge-deployable. Their method combined EMA modules, C2f-MSLR blocks and a newly developed loss function to improve small object detectors, and to cut down on the computational cost.

Lastly, Guan and Sun [10] formed a better YOLOv11n model that adds attention modules, StarBlock, and hypergraph-based feature fusion to expand the amount of defects at various scales and decrease the number of false positives. Their system showed significant gains on several evaluation metrics, which shows the possibility of hybrid attention-based systems to be efficient road surface monitors. The latest researches have gone on to investigate edge computing, lightweight architecture, and IoT-integration to detect road defects efficiently. Zhesterev et al. [11] created a convolutional neural network (CNN) that is implemented on unmanned aerial vehicles (UAVs) and is used to identify potholes and cracks. They have used EfficientDet to leverage transfer learning to realize automated video stream detection, which suggests that single-shot detectors can be used in large-scale monitoring. Nonetheless, the computational demands of UAV implementation indicate that the challenges of deploying UAVs require more efficient edge models. Mandal et al. [12] are suggesting a smart IoT-based pothole sensor and filling solution, in which Canny edge detector is used to detect potholes in real-time and an innovative two-layered pothole filling system incorporating a recycled plastic and concrete. This will not only solve the problem of road maintenance but also lead to sustainability of the environment. Although it is innovative, it is more of a repair of potholes as opposed to full-scale multi-class defect.

Pawar et al. [13] created a pothole detector and reporting system which is automated, allowing real-time identification of potholes, central storage of the data, and administrative visualization. Their system is marked by a reported detection accuracy of 87.67, which makes it clear that the combination of mobile devices and IoT platforms is of great use in managing urban roads. However, scaling to identify various defects other than potholes is also a shortcoming. Luo [14] proposed a better model of YOLO11 that improves the backbone feature extraction with receptive field attention and coordinated attention and brings MARA feature fusion in the neck network and SEAM feature in the detecting head. These optimizations led to high-performance small-target detection and mAP50 on the RDD2022 dataset indicating the usefulness of attention mechanisms and multi-scale features integration in complex road cases. Li et al. [15] developed LHA-Net, a model with low weight and high accuracy road defects detection network that can be deployed in resource-constrained environments. LHA-Net is able to offer direction-guided global feature modules, heterokernel local feature modules, and the weighted fusion of features, which provides competitive accuracy using significantly fewer parameters and reduces the computational load. The method proves that accuracy and efficiency can be balanced with the approach to the network design, which is a serious necessity of edge-based deployment of the IoT. Even with these developments, the present systems are not as practical as they need to be to detect multi-class faults in road surfaces in real-time and with depleted power in IoT systems due to single-class, heavy architectures, or cloud-assisted computations. This drives the creation of a TinyML-powered model that can operate across multiple classes, detect edges and run with low latency, which is the gap in the performance and deploy ability of smart city applications.

III. Proposed System

The proposed system is an edge-based optimized TinyML system, which aims at real-time and multi-class road surface faults detection in IoT-based settings. Figure.1 shows a proposed work hardware block diagram. The system combines the low-cost sensors, embedded computing, and lightweight machine learning to provide the ability to continuously monitor the urban and semi-urban roads without using cloud-based computing.

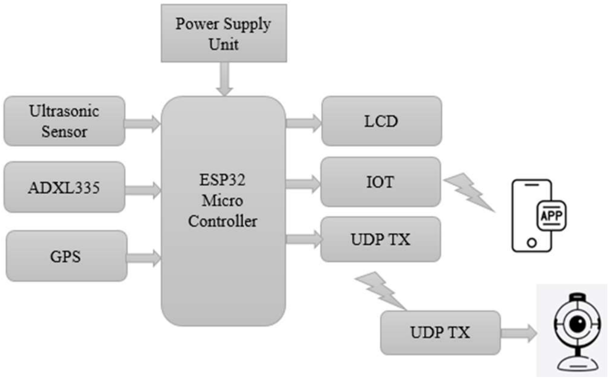

Figure.1 Proposed Work Architecture Diagram

The framework is composed of three main stages, such as data acquisition, edge-based processing, and IoT integration. To obtain the data, the system uses a camera-based module and a sensor array to record the visual characteristics of road surfaces and a sensor array of vibrations used to identify mechanical anomalies like potholes or rough edges. These non-homogeneous sensor inputs are combined with a lightweight sensor fusion algorithm that improves the strength of fault detection of diverse environmental factors and vehicle velocities. Figure.2 shows a proposed work architecture design. The combined data is handled in-device with a quantized MobileNetV2-based neural network optimized to run on the edges enabling the system to classify various types of faults- potholes, cracks, rough surfaces, normal segments, etc. at real-time speeds and consuming low energy. The model is quantized and pruned to decrease the footprint in memory as well as to minimize resource consumption without reducing its accuracy to achieve a high level of performance in resource-constrained scenarios.

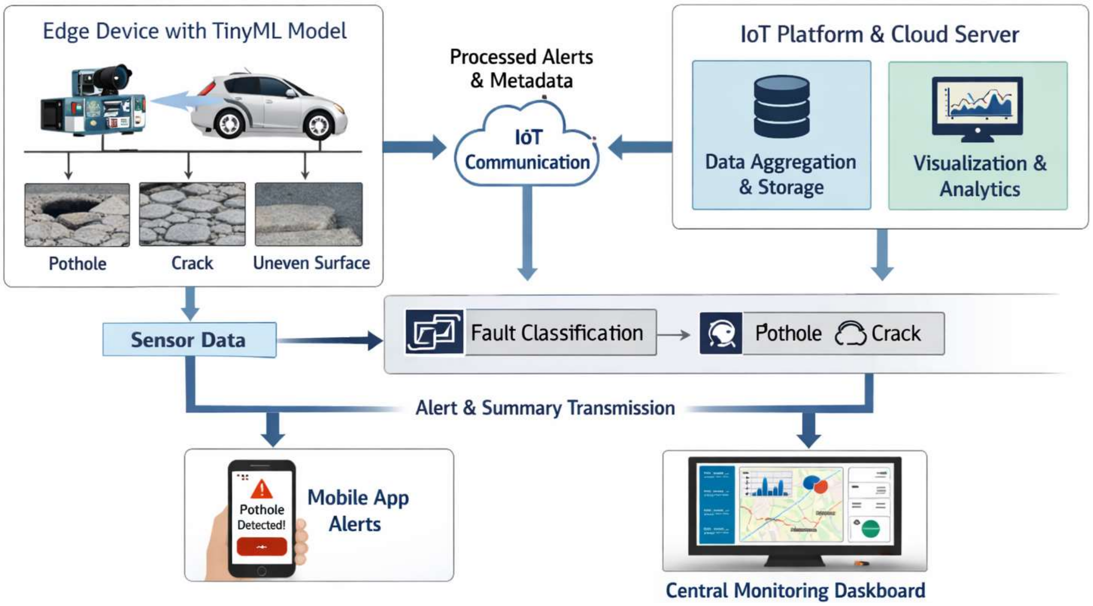

Figure.2 Proposed Work Architecture Diagram

After a fault has been detected by the system, a structured alert is sent with the type of fault, its location, and the confidence score that is sent to a centralized IoT platform. This makes it possible to visualize, monitor long term and plan predictive maintenance. The edge-based design reduces the level of network bandwidth by transmitting information that is processed instead of the raw information enabling it to be scalable to the entire city. On the whole, the suggested system is an effective, energy-efficient, and scalable system to manage smart infrastructure in a city, which offers a real-time automated monitoring of the road surface level, pre-emptive maintenance schedules, and better road safety to commuters.

IV. METHODOLOGY

The suggested methodology is aimed at developing an edge-optimized TinyML-based framework of real-time and multi-class road surface fault detection. The system has been developed to operate in resource-constrained IoT environments, so as to constantly monitor urban and semi-urban roads without involving computation in the cloud. The methodology will be divided into four principal phases: data acquisition, pre-processing and feature extraction, edge based TinyML model design, and IoT based alert and monitoring system.

A. *Data Acquisition*

The initial phase is the acquisition of road surface data by means of heterogeneous sensors. A high-resolution camera module records the visual characteristics of the road surface like cracks and potholes and uneven areas whereas a vibration sensor array is used to detect mechanical anomalies brought about by road diverticulum. The use of both vision and vibration information guarantees robust detection in diverse conditions of the road, light and the speed of the vehicle. Data is time stamped and geo-tagged so as to accurately localize faults. The camera captures high-resolution images $I(x,y)$ of road surfaces, where x and y represent spatial coordinates, and $I(x,y) \in [0,255]$ for grayscale intensity. Simultaneously, the vibration sensor records time-series acceleration signals $v(t)$ along the vehicle's travel direction, where t denotes time. The fusion of visual and mechanical signals provides complementary information that enhances detection robustness, particularly under varying lighting, weather, and speed conditions.

B. *Pre-processing and Feature Extraction.*

The raw sensor information is processed in advance to eliminate noise and normalize input information. Image data is converted to grayscale, resized and contrast changed whereas vibration signals are filtered with band-pass filters to preserve fault-specific frequencies. Lightweight convolutional operations are applied to image data to extract features, whereas statistical data (mean, variance, RMS) are applied to the vibration signal to extract features. Simple but effective sensor fusion algorithm is used to fuse together the processed features so that the reliability of the detections can be enhanced by using the complementary information of the two sensors.

For image data, pre-processing includes normalization and resizing to standard input dimensions for the neural network. Let the normalized image be denoted as $\tilde{I}(x,y)$, obtained as:

$$\tilde{I}(x,y) = \frac{I(x,y) - I_{\min}}{I_{\max} - I_{\min}} \qquad (1)$$

Vibration signals are pre-processed using a band-pass filter to extract fault-specific frequency components $v_f(t)$:

$$v_f(t) = \mathcal{F}^{-1}\{H(f) \cdot \mathcal{F}[v(t)]\} \quad (2)$$

where $\mathcal{F}$ and $\mathcal{F}^{-1}$ denote Fourier and inverse Fourier transforms, respectively, and $H(f)$ is the band-pass filter transfer function. Feature extraction is performed on $\tilde{I}(x,y)$ using lightweight convolutional layers, while vibration features include statistical descriptors such as root-mean-square (RMS), mean, and variance:

$$\text{RMS} = \sqrt{\frac{1}{T}\int_0^T v_f^2\,(t)dt} \qquad (3)$$

The image and vibration features are fused using a weighted sum to generate a composite feature vector F:

$$F = \alpha F_I + \beta F_v \qquad (4)$$

where F_I and F_v represent image and vibration feature vectors, and α\alphaα and β are empirically determined weighting coefficients.

C. Edge-Based TinyML Model Design

The fused and pre-processed characteristics are provided to an edge deployment optimized MobileNetV2-based neural network. The model conducts multi-classification of surface conditions in the roads into potholes, cracks, uneven parts and normal surface. Quantization minimizes memory footprint, whereas pruning eliminates redundant connections, which guarantees low-latency inference (< 40 ms) and low energy consumption (~1.8 W) on resource-constrained hardware.

The fused features F are input to a quantized MobileNetV2 neural network**,** which performs multi-class classification. The network maps F to predicted class probabilities P_c using a softmax function:

$$P_c = \frac{\exp(z_c)}{\sum_{i=1}^{C} \exp\,(z_i)} \qquad (5)$$

where z_c is the logit corresponding to class c and C is the total number of road fault classes. The predicted $\hat{y}$ is obtained as:

$$\hat{y} = \underset{c}{\operatorname{argmax}} P_c \qquad (6)$$

The model is pruned and quantized to reduce memory usage and inference latency, achieving real-time performance (<40 ms) with minimal energy consumption.

D. IoT Integration and Alert System

After identifying a road fault, a structured alert, including the type of fault, the score of confidence, and the geolocation is created and sent to a centralized IoT platform. The platform allows real-time monitoring, long-term monitoring and predictive maintenance planning. The system can deploy over a city-wide network without consuming raw data on the network as it only includes processed metadata, which allows it to be scaled. Upon detection, a structured alert vector $A = [\hat{y}, P_{\hat{y}},\text{lat,long}]$ is generated, where $\hat{y}$ is the predicted fault type, $P_{\hat{y}}$ its confidence score, and (lat,long) represent geolocation coordinates. This alert is transmitted to a centralized IoT platform, enabling real-time visualization, long-term monitoring, and predictive maintenance planning. By transmitting only metadata instead of raw images and vibration signals, the system achieves network efficiency and supports large-scale deployment across smart cities.

V. RESULT & DISCUSSION

This part is a critical analysis of the suggested Edge-Optimized TinyML Framework of Real-Time Multi-Class Road Surface Fault Detection. The experimental study is aimed at classification performance, edge performance in real time, computational performance, performance under road conditions and benefits of the IoT communication. The findings indicate that the suggested framework has a good balance in approaching accuracy, latency, and energy efficiency, and is therefore appropriate in the case of continuous use in smart city IoT infrastructures.

A. Experimental Dataset and Evaluation Protocol

The evaluation was carried out on a multi-modal dataset of its own, comprising 5,000 road samples of the surface with varied urban and semi-urban areas. In this dataset, there are four different classes, namely, potholes, cracks, uneven surfaces, and normal road segments. Data collection was conducted under different light conditions, speed of vehicles as well as textures of roads as a way of ensuring diversity and representativeness to the real world. To evaluate the performance objectively, the dataset was split into 70% training, 15% validation and 15% testing. The system was evaluated using standard evaluation metrics such as precision, recall, F1-score, accuracy, inference latency, and energy consumption to fully evaluate the system performance.

B. Multi-Class Classification Performance Analysis

The performance of the proposed TinyML model in terms of its classification of all categories of road surfaces is shown in Table I.

TABLE I. MULTI-CLASS CLASSIFICATION PERFORMANCE

Class	Precision (%)	Recall (%)	F1-Score (%)
Potholes	94.5	95.1	94.8
Cracks	92.3	91.7	92.0
Uneven Surfaces	91.2	90.5	90.8
Normal Surface	96.8	97.1	96.9
Average	93.7	93.6	93.6

The proposed framework has a total classification accuracy of 93.6% meaning it has good discriminative power on the various types of faults. Potholes have the best recalling characteristics because of their unique geometric depth and vibration features. Cracks and irregular surfaces have slightly lower values of recall, which is mainly because of slight visual differences and overlapping texture patterns. Nevertheless, the performance is strong, which proves the usefulness of sensor fusion and inference based on TinyML.

C. *Confusion Matrix and Error Analysis*

Misclassification patterns are better understood with the use of the confusion matrix shown in Figure.3.

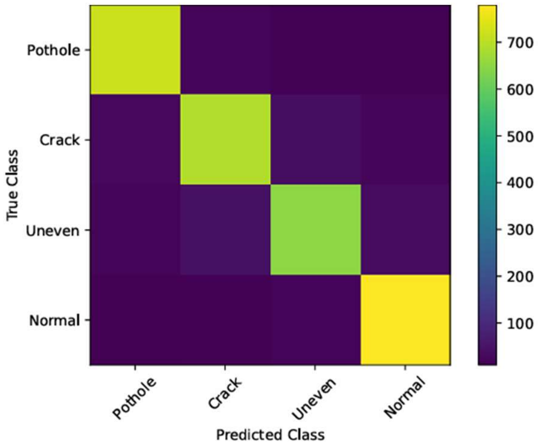

Figure.3. Confusion matrix for multi-class road surface fault detection.

The matrix shows that the bulk of misclassifications are between the cracks and uneven surfaces that tend to resemble visually when the asphalt is worn out. Notably, the rate of misclassification of normal road segments is low thus false-positive is low. This feature is especially significant in the case of municipal use since it does not alarm with unnecessary maintenance and resources distribution.

D. *Real-Time Edge Inference Performance*

One of the most important goals of the suggested framework is to obtain real-time inferences on resource-constrained devices.

TABLE II. EDGE INFERENCE AND RESOURCE UTILIZATION

Metric	Value
Average inference latency	35 ms
Throughput	28 FPS
Peak memory usage	210 MB
Average power consumption	1.8 W

Table II sums up the performance indicators that were witnessed on an edge device. The inference latency of 35 ms observed shows that the system only meets the real-time requirements, even at moderate and high vehicle speeds. The obtained throughput 28 frames per second allows to monitor road conditions with smooth and continuous monitoring. Captive power consumption also helps in long term usage in battery operated IoT systems.

E. *Impact of TinyML Optimization Techniques*

The base model was compared to the quantized and pruned one to assess TinyML optimization benefits. The comparison of latency of inferences is shown in Figure.4

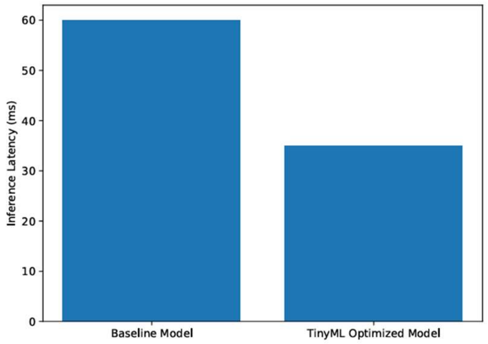

Figure.4 Inference latency comparison between baseline and TinyML-optimized models

Model quantization also minimized the numerical precision with little precision loss and structured pruning removed redundant parameters. All of these optimizations led to a model size reduction of about 62% and a 41% inference latency with a loss in accuracy of up to 1.2. These findings substantiate the fact that TinyML is required in the implementation of deep learning models on limited edge devices.

F. *Robustness Across Road Environments*

The system strength was tested in urban and semi urban settings. Figure.5 shows the accuracy of classification in various road environments. Urban roads have a bit better accuracy because fault structures are much better defined, whereas semi-urban roads have more variability of surface texture. Nonetheless, the difference in accuracy is not significant, which indicates the flexibility of the presented framework in various deployment proximities.

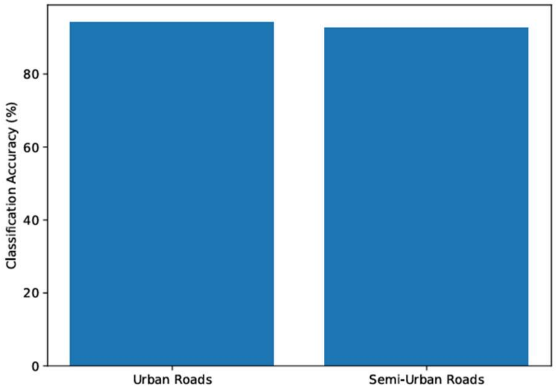

Figure.5. Accuracy comparison across urban and semi-urban road environments.

G. *IoT Communication and Bandwidth Efficiency*

One major strength of the framework proposed is its edge centric structure. In place of raw images and vibration signals, structured fault alerts with the labels of the classes, confidence levels, and geolocation information are propagated to the IoT platform. The estimated performance of this design is a reduction of network bandwidth utilisation by 70 75 percent relative to cloud based solutions. The unified IoT dashboard allows real-time visualization, past data trend analysis and predictive maintenance scheduling, and assists with data-driven infrastructure management.

H. Comparative Discussion and Practical Implications.

The proposed approach allows decreasing the latency, bandwidth consumption, and operational costs in comparison to the traditional cloud-based road monitoring systems considerably. The system is able to conduct uninterrupted, automated and objective evaluation of the road conditions unlike the manual inspection methods. The optimization of TinyML, the detecting and identifying faults in multiple categories, and the inference of edges in real-time makes the framework reasonable to the large-scale smart city applications. In general, the experimental findings prove that the suggested framework will be a reliable, energy-efficient, and scalable solution to real-time road surface fault detection that can be used to implement proactive maintenance policies and increase the road safety.

VI. CONCLUSION

In this paper, an edge-optimized TinyML road surface faults detection framework was presented in real-time and in IoT setting. It was shown with the proposed system that it is possible to provide a framework that is both accurate and reliable in monitoring road conditions on resource-limited edge devices without the need to process the data on a cloud platform. The experimental findings revealed that the overall classification accuracy of the experiment was 93.6, and the real time inference latency was 35 ms and the power consumption was low at 1.8 W which validates the feasibility of continuous deployment in smart city applications. The sensor fusion and TinyML optimization methods allowed creating powerful potholes, cracks, uneven surface, and normal road segment detection in various urban and semi-urban conditions. The value of this contribution is the multi-class fault detection, TinyML-powered edge inference, and IoT-powered monitoring having a single framework that can be scaled. The system saves a lot of network bandwidth as any alerts or metadata that are transmitted are processed before being sent to the network. The design helps in proactive planning of road maintenance, enhanced road safety and effective management of infrastructure at low costs. Future directions will aim at extending the framework to new fault patterns, adding new sensors like GPS and inertial devices and testing the performance of the framework on larger scale deployments to the city-wide. More optimization of ultra-low-power microcontrollers and integration with autonomous vehicle systems will also be discussed to make it more applicable to the real world.

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