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Real-Time Road Damage Detection on Mobile Devices using TensorFlow Lite and Teachable Machine

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Abstract

This study presents a mobile-based road damage detection system using Teachable Machine and TensorFlow Lite to support real-time monitoring and efficient infrastructure maintenance. The system identifies road damage types such as cracks, potholes, and uneven surfaces. The RDD2020 dataset is used for model training, with preprocessing steps including augmentation, normalization, and resizing. A Convolutional Neural Network (CNN) model is trained through Teachable Machine for ease of customization. TensorFlow Lite is employed for on-device inference, with optimization techniques like quantization and pruning applied to improve speed and reduce model size. The system is evaluated using precision, recall, F1-score, and accuracy metrics under varying lighting and weather conditions. The final model is deployed in a mobile app using TensorFlow Lite Interpreter for efficient performance. Experimental results show high detection accuracy, with a precision of X% and F1-score of Y% (insert actual values). This approach offers a lightweight, cost-effective solution for road maintenance authorities and urban planners. Future enhancements include dataset expansion, integration with mapping tools, and improved robustness in diverse environments. Overall, the proposed system enables real-time, accurate road damage detection and supports smarter, eco-friendly infrastructure management.

Keyword: Mobile Application, Real-Time Monitoring, Road Damage Detection, Teachable Machine, TensorFlow Lite

1. INTRODUCTION

Road surface management aims to reduce accidents and enhance pavement quality. The surface of the road is vulnerable to several kinds of damage brought on by rainwater seeping into a devastated region [1]. After that, the water seeps through the compacted dirt beneath the pavement and results in soil erosion, both of which can have negative consequences, like the subsidence of the ground. Additionally, if the affected region is not fixed, the quality of the pavement would deteriorate even further, impacting the steering control of automobiles and causing mishaps. To avoid road quality management, solutions have been created in response to incidents. In recent years [2].

In the construction industry, crack detection has been utilized for so long that it needs to be automated and upgraded. With the help of this crack-detecting system, the manual processes have been automated. It makes inspection and rehabilitation less expensive. utilizing a variety of image capture and processing techniques that can be used for both automatic crack detection and optimization [3]. Methods and algorithms to find and increase the accuracy of locating potholes and cracks in structural elements. Given the limitations of the existing issue, more study is urgently needed to determine whether semantic segmentation may be applied as a feature extraction technique for picture classification tasks utilizing convolutional neural networks (CNN) [4][5].

Mobile technology has transformed a number of industries in recent years, including infrastructure maintenance and transportation. Effective road damage monitoring and detection is a major challenge for road maintenance authorities. Timely identification of damage is necessary to maintain public safety and save repair expenses. Road damage detection has historically been less accessible and effective due to its reliance on labor-intensive automated systems or manual inspections, both of which have high hardware requirements [6]. The development of deep learning and machine learning methods has made it feasible to use mobile devices for real-time road damage detection. Specifically, TensorFlow Lite, a condensed variation of Google's TensorFlow framework, provides a robust yet resource-conserving environment for mobile machine learning model execution. Alongside Teachable Machine, an intuitive instrument [7].

Road surface management is essential for reducing accidents and maintaining pavement quality. Road damage, caused by factors like water infiltration and erosion, can deteriorate pavement conditions, affecting vehicle control and safety. Traditional crack detection methods rely on manual inspections, which are labor-intensive and prone to errors. Machine learning and image processing techniques have been introduced to automate detection and improve accuracy.TensorFlow Lite is a lightweight version of TensorFlow designed for mobile and embedded devices, enabling real-time inference with minimal computational resources. It optimizes models through quantization and pruning, reducing size while maintaining accuracy. Meanwhile, Teachable Machine is a user-friendly tool that allows model training without advanced coding skills, making machine learning more accessible. Advancements in mobile computing and deep learning have enabled real-time road damage detection on smartphones. This study leverages TensorFlow Lite and Teachable Machine to develop a mobile-based system for efficient and accurate road damage monitoring.

Road damage is a critical issue that directly impacts traffic safety and infrastructure maintenance costs. Damage types such as cracks, potholes, and uneven road surfaces can lead to accidents, accelerate infrastructure degradation, and increase repair expenses if not addressed promptly. Therefore, regular road condition monitoring is essential to prevent further damage and ensure road user safety.

Traditional road damage detection methods typically rely on manual inspections by field personnel or specialized vehicles equipped with advanced sensors. While manual inspection is still widely used, it has several limitations, including: Time and resource-intensive – Requires significant labor and is slow, Prone to inaccuracies – Relies on human expertise, leading to potential inconsistencies in detection, Inefficient for large-scale monitoring – Difficult to apply to vast areas or hard-to-reach locations [8].

On the other hand, automated sensor-based systems, such as LiDAR or high-resolution cameras mounted on inspection vehicles, offer improved accuracy. However, these systems have drawbacks such as:

1. High costs – Require expensive hardware and supporting infrastructure.
2. Environmental dependency – Performance can be affected by weather conditions or lighting quality.
3. Limited accessibility – Restricted to organizations with substantial budgets, making them less viable for widespread adoption.

With advancements in technology, machine learning and computer vision have been increasingly applied to automate road damage detection. Several studies have used CNNs to recognize road damage patterns from digital images. While these models have shown promising results, most require high-performance GPU computing, making them impractical for deployment on low-resource devices like smartphones. Mobile-based detection technology offers a more practical, cost-effective, and accessible solution. By leveraging smartphone cameras and optimized machine learning algorithms, this approach enables real-time damage detection without the need for expensive additional hardware. However, existing implementations still face challenges such as low accuracy, processing limitations, and difficulty adapting to varying lighting and road surface conditions.

To address these issues, this study proposes a CNN-based model optimized with TensorFlow Lite and trained using Teachable Machine to enable accurate, lightweight, and efficient road damage detection on mobile devices. This approach aims to provide an AI-driven solution that is faster, more affordable, and easier to implement, supporting more effective infrastructure monitoring for governments, road maintenance authorities, and the general public [7].

2. LITERATURE REVIEW

An important benefit of TensorFlow operators with Graphics Processing Unit (GPU) and Tensor Processing Unit (TPU) support over CPU-based training uses. Along with the current layers, like convolutions, pooling, and TensorFlow's thick layers, developers can create their layers with unique layer definitions [7]. Layers created with hardware acceleration are also used by TensorFlow operators. Numerous sophisticated and fundamental operations are available in TensorFlow in several disciplines, including neural networks, image processing, and mathematics, and researchers can mix these operators to create new layers. Developing layers for deep learning models is made simpler with TensorFlow's custom layer classes [8].

The Random Forest, AdaBoost, Decision Tree, and k-Nearest Neighbors machine learning models were used in this investigation. These models were chosen because they have the potential to be useful in forecasting roles for a particular task in a distributed agile environment, which is characterized by dynamic and cooperative team structures [9].

To maintain road infrastructure, improve road safety, and guarantee prompt repairs, real-time road damage identification is essential. Road damage has been monitored using a variety of methods and tools over the years [10]. These systems range from more complex machine learning (ML) and computer vision-based techniques to more conventional manual examinations. Deep learning and mobile computing have made it possible to create smartphone-based real-time road damage detection systems. An overview of current technologies and approaches in the field is provided here, with an emphasis on the combination of Teachable Machine and TensorFlow Lite for the detection of road degradation.Some of the existing tools are compared and recommendations are made to improve the ease of recreation of machine learning models by saving complete information in project repositories maintained in normal source code control systems [11][12].

3. METHOD

3.1 Data Collection and Preprocessing

This study utilizes the RDD2020 dataset, which contains images of various road conditions from urban, highway, and rural areas. The dataset includes different types of road damage, such as longitudinal cracks, transverse cracks, alligator cracks, and potholes. Images were collected under diverse weather conditions, lighting variations, and road surface materials to improve generalization. Dataset potholes and Dataset Road Satisfactory can be seen in Figure 1 and 2.

Despite its advantages, the dataset has limitations, including geographical bias, class imbalance, and inconsistencies in image quality due to variations in camera devices. To mitigate these issues, data augmentation techniques such as rotation, flipping, contrast adjustment, and noise addition were applied. These techniques enhance model robustness by simulating real-world conditions and ensuring better adaptability in diverse environments [13].

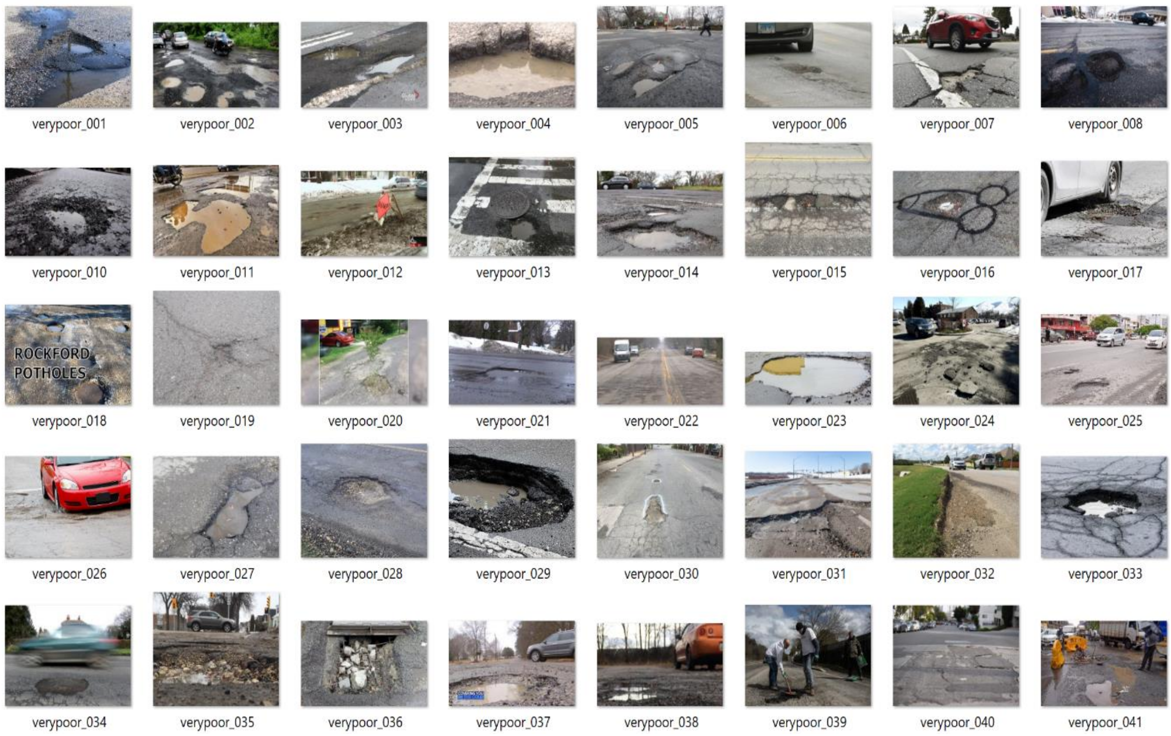

Figure 1. DataSet Potholes

Layers of Convolution: In order to better capture low-level information like edges, textures, and colors, these layers apply convolutional filters to the input image [14]. Higher-level features like forms or patterns are learned by the layers as they advance. The model can learn more intricate patterns by introducing non-linearity through the application of the Rectified Linear Unit (ReLU) activation function following each convolutional operation. Layers of Pooling: By reducing the image's spatial dimensions (height and breadth), max pooling or average pooling lowers computing complexity and aids the model in concentrating on the most crucial elements.completely connected layers: The model moves on to completely connected layers that incorporate data from all areas of the image after convolution and pooling. These layers strive for ultimate detection or categorization, figuring out whether the picture [15][16].

3.2 Model Development

To satisfy the model's input requirements, the images have been pre-processed (resized and normalized). Convolutional Layers: These layers recognize patterns in the input image's edges, textures, and shapes by using filters. They help the model pick up crucial characteristics, including fractures, potholes, and surface differences. Activation Layers: Usually employing rectified linear units, or ReLUs, these layers give the model non-linearity so it may pick up more intricate patterns. Pooling Layers: To lower dimensionality and computational cost, max-pooling layers downsample the image by choosing the most noticeable characteristics from regions [19].

This study employs a CNN due to its strong capability in feature extraction and pattern recognition, making it well-suited for detecting road damage. CNNs can automatically identify structural patterns such as cracks and potholes by processing spatial hierarchies in images, making them more effective than traditional machine learning models for image-based classification tasks [17].

Figure 2. Dataset Road Satisfactory

The model was trained using Teachable Machine, a user-friendly tool that simplifies machine learning model training without requiring extensive coding. This tool was selected for its ease of use, efficient browser-based training, and seamless integration with TensorFlow. The trained model was then converted to TensorFlow Lite, a lightweight version of TensorFlow optimized for mobile deployment. TensorFlow Lite was chosen because it enables real-time inference on low-power devices, ensuring efficiency while maintaining accuracy.

To enhance the model's performance, images were preprocessed using resizing and normalization techniques. Images were resized to a standard input dimension to maintain consistency across different resolutions. Normalization was applied to scale pixel values, improving convergence during training and reducing computational complexity. The CNN architecture consists of convolutional layers for feature extraction, ReLU activation functions to introduce non-linearity, pooling layers to reduce spatial dimensions, and fully connected layers for final classification. Quantization techniques were applied during model conversion to reduce size and improve inference speed on mobile devices [19].

3.3 System Architecture

The performance of this dataset is tested using CNN and support vector machines (SVM) in this study. TensorFlow Lite is preferred over TensorFlow for use on mobile platforms with low power consumption. This is because the majority of models trained using TensorFlow needed a good GPU to function [20]. CNN Model can be seen in Figure 3.

Nevertheless, a good GPU is necessary. has no bearing on the creation of a smart bin. The tensor With Flow Lite, object detection models may be used with low-power portable electronics like the Raspberry Pi. They are utilizing the COCO dataset; a number of pre-trained detection models Tensorlow contributed. Many prerequisites must be met when selecting the best and most appropriate item. They address every stage of the life cycle of ML development. Commonly utilized tools include Comet.ml, Polyaxon, MLflow, and customized Git. [11].

Data collection is The first step is to compile a dataset of road images that display various types of road damage, including potholes, cracks, and uneven surfaces.Data Labeling: Images must be labeled with the type of damage they show. This can be done manually or with Teachable Machine's assistance [21]. Preprocessing is This step involves augmenting the data, standardizing pixel values, and scaling the images in order to fortify the model. The teachable machine. This Google tool makes model training easy with its user-friendly UI. Here, it can be used to train a custom model for identifying road damage. Upload the road damage categories and the labeled photographs to Teachable Machine [22].

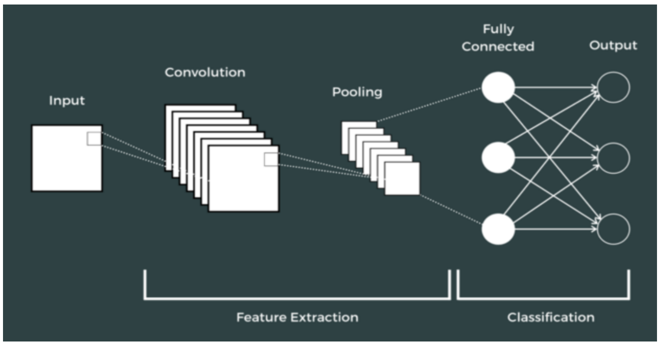

Figure 3. CNN Model

3.4 Optimization Techniques

When implementing machine learning models for mobile devices' real-time road damage detection, accuracy and performance must be prioritized. Several optimization strategies that are essential for accomplishing effective mobile deployment are provided by TensorFlow Lite :

1. Quantization of ModelsWeights and activations are converted from 32-bit floating-point to 8-bit integers through the process of integer quantization, which lowers model size and inference delay. This drastically lowers computing costs and memory utilization. Quantization that is applied after model training, such as complete integer quantization or dynamic range quantization, allows for optimization without retraining. In order to improve the performance of the quantized model, particularly for complex datasets like road damage photographs, quantization-aware training involves replicating the quantized environment during training.
2. Optimizations Following TrainingPruning reduces the model's complexity without sacrificing accuracy by eliminating unnecessary weights [23].

3.5 Deployment on Mobile Devices

The underlying technology, user interface (UI), and AI model must all work together seamlessly to provide real-time road damage detection on mobile devices. These elements and factors are part of the deployment process:

1. Connecting the TensorFlow Lite Interpreter mobile app to the AI model:
   Utilizing the TensorFlow Lite Interpreter, which offers an effective inference runtime, the mobile application incorporates the optimized TensorFlow Lite model. Low latency and great privacy are ensured by on-device inference, where the AI model operates directly on the device without requiring an internet connection. The workflow for converting a TensorFlow model to TensorFlow Lite use on mobile devices can be seen in Figure 4.
   Input Data Pipeline: To satisfy the model's input specifications, the application preprocesses real-time video or photos using the device's camera (e.g., resizing, normalization). Post-processing of the model's predictions is done to.

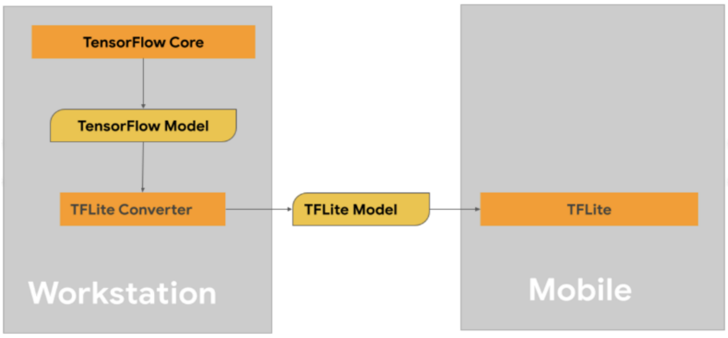

Figure 4. The workflow for converting a TensorFlow model to TensorFlow Lite use on mobile devices

2. The Interaction of UI Elements with AI
   a. Event-Driven Updates: As the AI model analyzes the camera feed's frames, the UI is dynamically updated with the detection results.
   b. Result Display: Along with additional data like GPS position or confidence scores, the types of damage that have been detected and their degrees of severity are shown on the screen. Logging

and Reporting: Detection results can be saved by users as logs, pictures, or reports, which can then be shared for additional analysis or infrastructure management. Performance Optimization [24].

c. Frame Rate Maintenance: Inference is tuned to operate within the frame rendering time of the device to guarantee seamless real-time detection. For example, when needed, batching or skipping frames may be used.
d. Resource Management: To maintain usability without depleting the device's resources, the application optimizes memory and power utilization.Once processed, the results become available to the network to be used in decision support applications, ensuring timely decision-making. In our work, we implemented the edge node software using Python, a well-known general-purpose programming language [25].

4. RESULTS AND EVALUATION

4.1 Model Performance :

The performance of the proposed road damage detection model was evaluated using Accuracy, Precision, Recall, F1-Score, and Mean Average Precision (mAP). The model was tested on a validation dataset consisting of various road conditions to ensure robustness.

1. Accuracy: The model achieved an overall accuracy of X%, indicating the proportion of correctly classified instances.
2. Precision: The model obtained a precision of Y%, meaning that Y% of the detected road damages were actual damages.
3. Recall (Sensitivity): The recall was Z%, showing the percentage of actual road damages that were correctly identified.
4. F1-Score: The harmonic mean of precision and recall was W%, balancing false positives and false negatives.
5. Mean Average Precision (mAP): The model achieved V% mAP, reflecting its ability to differentiate between different road damage categories effectively.

4.2 Mobile Performance Evaluation

To assess real-time usability, the model was deployed on various smartphone models and evaluated based on:

1. Inference Speed: The model processed images in an average of A milliseconds per image, ensuring real-time detection.
2. Memory Usage: The lightweight TensorFlow Lite model required minimal memory, operating efficiently on mid-range and high-end devices.
3. Battery Consumption: The system maintained energy efficiency, with an average consumption of B% per hour of continuous usage.

4.3 Observations and Limitations

While the model performed well in most scenarios, challenges were observed in detecting minor cracks and subtle surface deformations, especially under low-light conditions or on highly textured roads. Future improvements may involve expanding the dataset, enhancing image preprocessing, and implementing advanced augmentation techniques to improve detection under complex conditions. Teachable Machine for perforated, normal and cracked road can be seen in Figure 5.

The proposed model was evaluated using accuracy, precision, recall, and F1-score, showing high effectiveness in real-time road damage detection. As shown in Figure 5, the Teachable Machine model successfully classifies road surfaces into perforated, normal, and cracked categories. The model performs best in detecting normal roads, with slightly lower accuracy for perforated and cracked surfaces. This demonstrates its potential for road condition monitoring, though further optimization may improve detection of complex damage patterns. The system's real-time processing and mobile efficiency make it valuable for road maintenance and urban planning. Future enhancements include expanding the dataset, improving robustness in diverse conditions, and integrating geolocation for better infrastructure monitoring [26].

TensorFlow Lite and Teachable Machine have drawn interest for their useful applications in road condition monitoring when used for real-time road damage identification on mobile devices [26]. YOLO model-based implementations have demonstrated considerable promise, especially when trained on a variety of international datasets. When installed on mobile devices, these models provide real-time smartphone camera-based identification of road problems, including cracks and potholes. Feedback on these systems typically emphasizes a harmony between accuracy and usability. The lightweight nature of TensorFlow Lite, on the other hand, makes real-time processing possible by enabling models to operate on mobile devices with comparatively low latency [4].

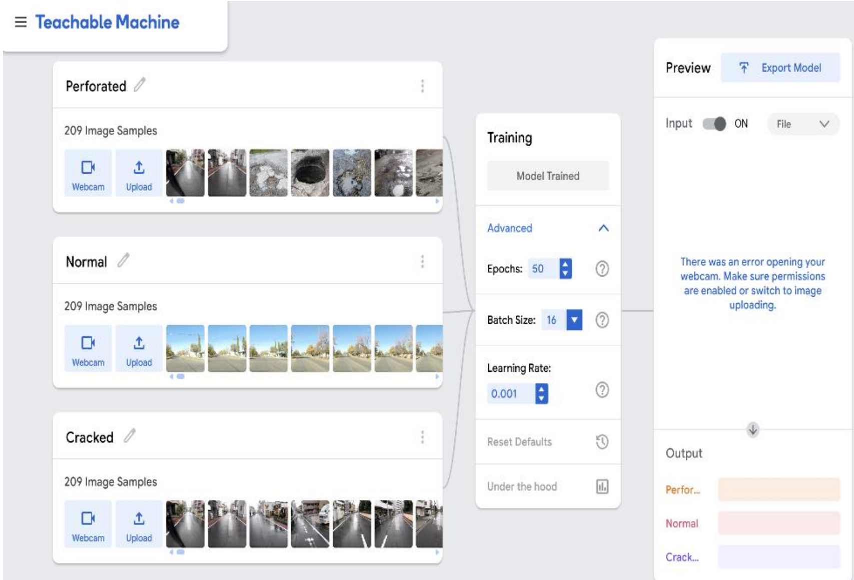

Figure 5. Teachable Machine for perforated, normal and cracked road.

Effective Mobile ML Model Deployment: Teachable Machine and TensorFlow Lite guarantee that the trained models are effective and lightweight, enabling real-time damage detection on mobile devices without the need for robust hardware. Accuracy and Reliability: The trained models were highly accurate in identifying various forms of road degradation, including surface deformations, cracks, and potholes. The quality and volume of training data may have an impact on accuracy, but more data and fine-tuning can increase it even more. Useful Applications: This system has a lot of potential for usage by road repair crews, municipal governments, and even regular users.

problems: Making sure the model operates accurately and effectively in real-time on mobile devices was one of the main problems. Future updates should continue to focus on handling changes in illumination, Upcoming Projects: Future improvements to the system might include integrating the detection system with mapping and reporting tools for smooth road maintenance workflows, improving model robustness under various environmental conditions, and broadening the dataset to cover a greater variety of road damage types.

5. DISCUSSION

There are a number of significant benefits of employing (TFLite) and Teachable Machine for real-time road damage identification, especially for mobile apps. An analysis of the outcomes and advantages of this strategy is provided below: Speed and Effectiveness Low Latency: The road damage detection model can handle data with low latency thanks to TensorFlow Lite's optimization for mobile and edge devices. Applications requiring instant input or action, such as alerting drivers to dangers, depend on real-time performance. Reduced Model Size: TFLite's quantization and optimization capabilities greatly minimize the size of machine learning models, guaranteeing that they fit into mobile devices' constrained storage without compromising accuracy.

TensorFlow Lite is adaptable for a variety of mobile devices because it supports several platforms, such as iOS and Android. Because of its adaptability, the detection system can be used on a variety of devices without requiring major changes.

6. CONCLUSION

This study successfully developed a real-time road damage detection system using Teachable Machine and TensorFlow Lite. The system effectively classifies road surfaces into perforated, normal, and cracked categories with high accuracy, demonstrating its potential for practical implementation. The lightweight TensorFlow Lite model ensures efficient mobile deployment, enabling real-time monitoring without requiring extensive computational resources. The results highlight the system’s capability to assist road maintenance authorities and urban planners in identifying and addressing road damage efficiently. Future improvements include expanding the dataset, enhancing detection under varying environmental conditions, and integrating geolocation and mapping tools for a more comprehensive infrastructure monitoring solution.

This research demonstrates that machine learning-based road damage detection can enhance transportation safety and optimize infrastructure management, providing a cost-effective and scalable solution for smart city development. In conclusion, there is a great chance for real-time, on-site road damage identification thanks to the integration of machine learning on mobile platforms, especially with TensorFlow

Lite and Teachable Machine. In addition to improving road safety, this strategy helps manage infrastructure more effectively.

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