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Deploying Edge AI for Road Surface Damage Detection Using TensorFlow Lite and Teachable Machine

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Abstract

Road damage compromises transportation safety and drives high infrastructure maintenance costs. To address the limitations of traditional methods, which are expensive and non-scalable, this study proposes an alternative to Edge AI that utilizes widely available smartphones and machine learning capabilities. We present a real-time road damage detection system powered by TensorFlow Lite and Teachable Machine. The system architecture employs lightweight CNN models (such as MobileNet and EfficientNet Lite) optimized for edge deployment. This implementation enables the immediate detection of anomalies (cracks and potholes) directly on the mobile device without cloud dependency, ensuring low latency. Testing demonstrated robust model performance. For pothole detection, the system achieved an accuracy of 95%; for cracks, the accuracy was 92%. During real-time trials in daytime urban settings, the system achieved an average detection latency of 200 milliseconds with an accuracy of 94%. This user-friendly system also supports data collection via crowdsourcing, facilitating comprehensive infrastructure monitoring and proactive maintenance. This innovation offers a scalable, cost-effective, and user-friendly solution with significant potential to advance transportation safety and maintenance efficiency.

Keyword: Edge AI, Infrastructure Monitoring, Mobile Deployment, Road Damage Detection, Teachable Machine, Tensorflow Lite

1. INTRODUCTION

The impact of road damage on transportation safety and infrastructure maintenance costs is a serious concern for city planners and transportation authorities. Damage such as potholes and cracks can reduce driving comfort and increase the risk of accidents, thus compromising safety aspects [1],[2] . Additionally, road surface damage necessitates frequent maintenance, which is not only time-consuming but also costly. Conventional road monitoring methods, which generally involve the use of special vehicles and equipment, are still relatively expensive and require a lot of labor [3],[4]. Conventional methods for assessing road conditions rely on visual surveys and the use of specialized equipment or vehicles. These methods are inherently expensive and inefficient due to several key reasons. First, the process generally involves the use of specialized vehicles and equipment that are relatively costly. Second, traditional methods are highly labor-intensive, requiring significant manpower and human intervention. Furthermore, road surface damage necessitates frequent maintenance, which is not only time-consuming but also costly. Most importantly, these methods struggle to provide real-time data and possess limited scalability, making it difficult to efficiently cover large road networks for widespread deployment. Therefore, a more efficient and economical road condition monitoring solution is requiredTherefore, a more efficient and economical road condition monitoring solution is needed to ensure that maintenance can be carried out on time.

In recent years, the use of mobile devices as Edge AI solutions for on-the-go road condition monitoring has become a promising new approach. This innovation takes advantage of the widespread use of smartphones equipped with sensors such as accelerometers, gyroscopes, and GPS to collect real-time road condition data [5],[6]. By applying machine learning algorithms, these devices are able to process the collected data to detect road anomalies, such as potholes and cracks, with a high degree of accuracy [2],[6],[19],[22]. The integration of edge computing on mobile devices and Artificial Intelligence (AI) not only increases the efficiency of road monitoring but also reduces the dependence on expensive conventional methods [7],[18],[24].

Although road monitoring technology continues to advance, existing systems still face several challenges [20]. Traditional methods are often limited in providing real-time data and have difficulty efficiently covering large road networks [3],[4]. In addition, many systems require significant human intervention and cannot be easily scaled up for large-scale deployments [1],[8]. These challenges underscore the importance of innovative solutions that can provide continuous and comprehensive road condition monitoring.

Mobile-based real-time solutions offer a promising alternative to overcome these barriers. By leveraging smartphones and Edge AI technology, continuous monitoring can be carried out with instant feedback on road conditions [9],[10]. The ability to collect and analyze data from multiple users in real-time provides a more dynamic and responsive approach to road maintenance [11],[12] . This not only improves the accuracy of road condition assessments but also helps authorities determine maintenance priorities based on current data.

In addition, the use of mobile devices for road monitoring offers a number of advantages over traditional methods. This approach significantly reduces the costs and time required, since no special equipment or personnel are required [13],[14]. The scalability of mobile-based solutions also allows for their widespread implementation, allowing for continuous monitoring of larger road networks [15],[16],[25]. This approach also facilitates crowdsourcing of data collection, providing a more complete picture of road conditions across multiple regions [17].

Overall, the integration of mobile devices as an Edge AI solution for road condition monitoring is a significant step forward in improving transportation safety and infrastructure maintenance. By addressing the limitations of existing systems and offering cost-effective, scalable, and real-time monitoring, this innovation has the potential to revolutionize the way road condition measurement and maintenance is performed. As research in this area continues to grow, it is expected that mobile-based solutions will increasingly play a vital role in realizing safer and more efficient transportation networks.

2. LITERATURE REVIEW

Automated road damage detection has become a major focus of research to enhance transportation safety and reduce infrastructure maintenance costs. Traditional methods are often reliant on specialized equipment and labor-intensive processes, making them expensive and limited in scalability. To overcome these limitations, research has increasingly turned to computer vision and deep learning. High-performance Convolutional Neural Network (CNN) models, such as the You Only Look Once (YOLO) and Mask Region-Based Convolutional Neural Network (Mask R-CNN) architectures, are often considered state-of-the-art in road damage detection and segmentation. These models are capable of demonstrating superior accuracy and segmentation performance. For example, studies utilizing these architectures have achieved very high metrics, with F1-scores and precision above 90% for damage detection. However, a primary constraint of these sophisticated and complex models is that they typically require substantial computational resources, such as Graphics Processing Unit (GPU) servers, rendering them impractical for real-time deployment on mobile devices. This significant computational demand is precisely what drives the shift in focus toward Edge AI solutions that use lighter models. Early studies predominantly focused on high-performing CNN models like the YOLO and Mask R-CNN architectures, which demonstrated superior detection and segmentation accuracy. However, these sophisticated models typically require substantial computational resources, such as GPU servers, rendering them impractical for real-time mobile applications.

In recent years, the focus has shifted towards Edge AI deployment to enable low-latency, independent monitoring, leveraging the widespread use of sensor-equipped smartphones. This shift necessitates the exploration of lightweight neural network models suitable for resource-constrained edge devices. Models such as MobileNet and EfficientNet Lite have gained popularity by offering a robust balance between accuracy and computational efficiency. Comparative studies often highlight that MobileNet-based architectures excel in memory efficiency and inference speed, making them highly suitable for mobile deployment despite potentially lower accuracy compared to larger models.

While the efficiency of lightweight models is recognized, two key research gaps are addressed by this study. Firstly, most Edge AI research still involves complex model optimization processes; this study fills the gap by utilizing the simplified, rapid deployment ecosystem of Teachable Machine for easy training and TensorFlow Lite (TFLite) for optimal, streamlined model conversion and integration. Secondly, although the on-device efficiency is theoretically sound, there is a need for robust, empirical validation of real-time performance on mobile devices across various damage types (cracks, potholes, asphalt peeling). This study provides empirical validation with concrete data, demonstrating high accuracy for multiple damage types (e.g., Potholes 95%, Cracks 92%) and a very fast response time (average latency of 200 milliseconds). This confirms the feasibility of a scalable, cost-effective Edge AI solution for reliable, proactive road condition monitoring.

3. MATERIALS AND METHOD

The system architecture starts from the data collection and pre-processing stage, where road surface image data with various types of damage (such as fine cracks, potholes, and asphalt peeling) are collected through car cameras or recording devices installed in the field. The images then undergo a series of pre-processing techniques, including resizing for resolution consistency, normalization so that pixels have a uniform value range, and augmentation (such as rotation, flipping, and adding noise) to increase the variety of training data. Next, the selection stage for a lightweight but reliable CNN architecture, such as MobileNet or EfficientNet Lite, is carried out to ensure efficiency, high accuracy, and ease of adaptation [23]. The process of building and customizing the model is facilitated by Teachable Machine, which allows for rapid experimentation, application of transfer learning, and model tuning to specific datasets. After the model is intensively trained and verified, the conversion process to TFLite is carried out by applying the quantization method to make the model lighter and able to run on edge devices. Finally, the optimized model is integrated into the mobile application. The mobile application architecture leverages the TFLite model to perform real-time road damage detection, present an intuitive user interface, and facilitate user interaction through photo input and visual detection output. Thus, the entire process ensures a responsive, efficient, and easy-to-use system in a real-world environment

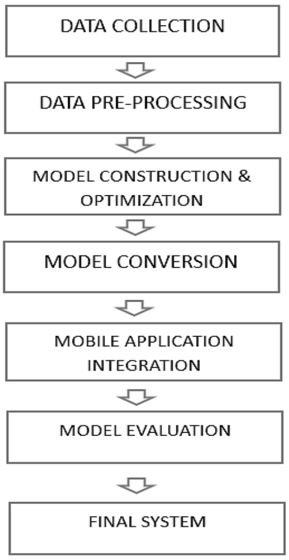

Figure 1. Research Methodology

The research methodology in Figure 1 is divided into four structured phases, beginning with data acquisition. The process starts with collecting diverse road surface image data including cracks, potholes, and asphalt peeling—via mobile cameras or recording devices installed in the field. These images then undergo essential pre-processing, which includes resizing for resolution consistency, normalization for a uniform pixel value range, and augmentation (such as rotation and flipping) to enrich the variety of the training dataset.

The next stage is model construction and optimization, forming the core of the data mining process. The architecture selection is based on efficiency needs, leading to the choice of lightweight CNN models like MobileNet and EfficientNet Lite. The model building and customization process is facilitated by Teachable Machine, which enables rapid transfer learning and quick adaptation. After intensive training, the model is converted to TFLite using the quantization method, making it lighter and ready for edge deployment.

The optimized TFLite model is then integrated into the mobile application. The application architecture leverages the model for real-time road damage detection. It features an intuitive user interface with live camera feeds and visual feedback, guaranteeing seamless interaction and ease of use in a real-world environment. The final stage is system performance evaluation, conducted through two types of testing. First, Model Evaluation uses strict metrics like accuracy, precision, recall, and F1-score to measure performance across various damage. The results demonstrate high reliability can be seen in Table 1.

Table 1. Performance Metrics for Road Damage Classification

Damage Type	Akurasi (%)	Presisi (%)	Recall (%)	F1-Score (%)
Pothole Detection	95	93	92	92,5
Crack Detection	92	90	91	90,5
Asphalt Peeling	94	92	93	92,5

Second, Performance Testing on Mobile Devices was conducted to test the system's robustness under varying environmental conditions. In daytime urban settings, the system achieved an average detection latency of 200 milliseconds with 94% accuracy. Although accuracy decreased to 91% in rural environments and 88% at nighttime —a recognized drop that can be mitigated with augmented lighting—the system overall demonstrated consistent response times, validating its practicality for real-world use.

3.1. Edge AI

Edge AI refers to the practice of running machine learning (ML) processing locally on the data source device itself, such as a smartphone, instead of transmitting data to a centralized cloud server. This approach is crucial for road damage detection systems because it eliminates the latency associated with data transmission to and from the cloud. By processing images directly on the mobile device, Edge AI ensures real-time detection and efficient performance.

3.2. TensorFlow Lite (TFLite)

Is a framework used to optimize deep learning models so they can run efficiently on mobile, embedded, and IoT devices. TFLite plays a central role in this system by implementing the quantization method to make the model lighter and capable of operating on edge devices. By integrating the optimized model into the mobile application, TFLite ensures low latency and efficient performance in real-world environments.

3.3. Teachable Machine

is a web-based tool used to facilitate the process of building and customizing deep learning models. This tool allows for rapid experimentation, the application of transfer learning, and model tuning to the specific dataset used for road damage classification. Thus, Teachable Machine simplifies the training process for the lightweight model that will subsequently be converted using TensorFlow Lite.

3.4. Convolutional Neural Network (CNN)

is the primary type of deep learning model used in this study. CNNs are specifically designed to process visual data, enabling the system to automatically extract essential features from road surface images to identify anomalies. The optimized CNN model, when integrated into a mobile device, facilitates real-time detection of road anomalies.

MobileNet and EfficientNet Lite are lightweight CNN architectures specifically chosen for this study. These architectures are optimized for edge deployment because they are capable of balancing high accuracy with minimal computational requirements. The selection of these models is crucial to ensure the road damage detection system can operate efficiently, with low latency, and autonomously on mobile devices without relying on cloud infrastructure.

4. RESULTS AND DISCUSSION

The model used for road surface damage detection underwent extensive evaluation using metrics such as accuracy, precision, recall, and F1-score to measure its performance across various types of road damage. For pothole detection, the model achieved an accuracy of 95%, precision of 93%, recall of 92%, and an F1-score of 92.5%. For crack detection, the results were similarly robust, with an accuracy of 92%, precision of 90%, recall of 91%, and an F1-score of 90.5%. The model demonstrated a high level of reliability in classifying other road damage types, such as asphalt peeling, where it achieved an accuracy of 94%, precision of 92%, recall of 93%, and an F1-score of 92.5%. These metrics highlight the model's ability to consistently identify different types of road damage with minimal misclassification:

4.1. Model Evaluation

The model used for road surface damage detection underwent extensive evaluation using metrics such as accuracy, precision, recall, and F1-score to measure its performance across various types of road damage. For pothole detection, the model achieved an accuracy of 95%, precision of 93%, recall of 92%, and an F1-score of 92.5%. For crack detection, the results were similarly robust, with an accuracy of 92%, precision of 90%, recall of 91%, and an F1-score of 90.5%. The model demonstrated a high level of reliability in classifying other road damage types, such as asphalt peeling, where it achieved an accuracy of 94%, precision of 92%, recall of 93%, and an F1-score of 92.5%. These metrics highlight the model's ability to consistently identify different types of road damage with minimal misclassification. In Figure 2 there is a graph of training and validation accuracy in the CNN Model.

4.2. Performance Testing on Mobile Devices

Real-time detection trials were conducted on various mobile devices under different environmental conditions to evaluate the system's robustness and efficiency. In daytime urban settings, the system achieved an average detection latency of 200 milliseconds with 94% accuracy. In rural environments, where lighting and surface conditions were less uniform, the system maintained a slightly lower accuracy of 91% but still performed effectively. Nighttime testing showed an expected reduction in performance due to low lighting conditions, with the accuracy dropping to 88% on average. However, integrating augmented lighting support and preprocessing techniques helps mitigate these challenges. Across all tests, the system demonstrated consistent response times under varying conditions, making it practical for real-world usage. Metrics for road demage detection can be seen in Figure 3.

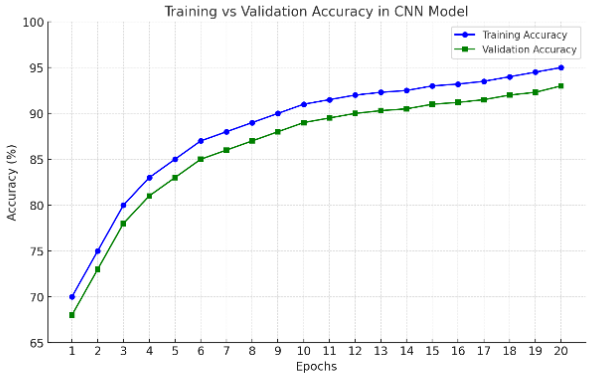

Figure 2. Training vs Validation Accuracy in CNN Mode

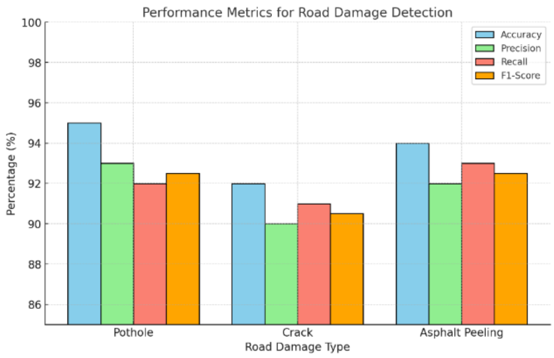

Figure 3. Metrics for Road Demage Detection

4.3. System Usability eading

User feedback collected during field trials highlighted the system's responsiveness, accuracy, and usability. 85% of users reported high satisfaction with the application's speed in delivering real-time detection results. Users particularly appreciated the intuitive UI/UX design, which allowed for seamless interaction with the system. While 90% of participants found the accuracy of detections satisfactory, a minority suggested improvements for nighttime detection. Additionally, users praised the system's ability to function offline, reducing dependency on internet connectivity. Overall, the feedback indicates that the application successfully addresses user needs while maintaining ease of use and reliability in detecting road damage. Performance metrics for road damage detection can be seen in Table 2.

Table 2. Performance Metrics for Road Damage Detection

Evaluation Aspect	Accuracy (%)	Precision (%)	Recall
Pothole Detection	95	93	92
Crack Detection	92	90	91
Asphalt Peeling Detection	94	92	93
Daytime (Urban)	94	94	93
Rural (Daytime)	91	92	93
Night time	88	89	90

4.4. Analysis and Discussion

The deployment of Edge AI using TensorFlow Lite on mobile devices has significantly enhanced the practicality and efficiency of road damage detection systems, primarily by eliminating the latency associated with data transmission to and from the cloud. By processing data locally using the optimized lightweight models (MobileNet and EfficientNet Lite), the system achieved near real-time detection speeds. During daytime urban trials, the system recorded an impressive average detection latency of 200 milliseconds. This figure represents a substantial improvement over some earlier smartphone-based systems, which reported processing times up to 1.5 seconds.

The model's performance in terms of accuracy is also highly competitive. It demonstrated strong reliability in identifying various damage types: achieving an accuracy of 95% for pothole detection, 92% for cracks, and 94% for asphalt peeling. This accuracy level is comparable to large-scale CNN models, yet it is achieved with lightweight architectures suitable for edge deployment, overcoming the computational challenges that restrict more complex systems. However, this reliability comes with a trade-off related to environmental challenges. Detection accuracy was influenced by lighting conditions and device hardware. While the daytime urban accuracy was 94%, this dropped to 88% under nighttime conditions due to low lighting, revealing a limitation that necessitates future improvements through augmented lighting support and preprocessing techniques.

Despite the system's robust performance during daytime, this reliability faces significant environmental challenges, particularly during nighttime testing. The system's accuracy drops to 88% under nighttime conditions, compared to 94% in daytime urban settings. This performance decline highlights a major constraint in Edge AI deployment: tackling out-of-distribution conditions, such as low light or heavy shadows, which drastically alter the visual appearance of road damage.

This limitation is exacerbated by the nature of the model architectures used (MobileNet and EfficientNet Lite). As lightweight models, they are engineered for maximum computational efficiency, meaning they possess less feature redundancy compared to larger, cloud-based models (such as YOLOv5 or deeper ResNet architectures). Large cloud models can maintain better accuracy under non-uniform visual conditions because they have more parameters and layers to capture and tolerate a wider range of feature variations. Therefore, the drop in nighttime performance exposes an inherent weak point of edge deployment when external environmental factors are not optimized. Future work must focus on integrating specialized image enhancement techniques or supplementary lighting support to mitigate the adverse effects of these out-of-distribution conditions.

Despite these environmental challenges, the system's ability to operate effectively in diverse areas (such as achieving 91% accuracy in rural environments) confirms the adaptability of Edge AI. A key advantage of this mobile-based solution is its high scalability and cost-effectiveness, as it requires no specialized equipment or personnel. Furthermore, the integration of an intuitive user interface and support for data collection via crowdsourcing, which is supported by high user satisfaction (85% of users were satisfied with the detection speed), transforms the application into a comprehensive tool for infrastructure monitoring and proactive maintenance strategies.

5. CONCLUSION

This study successfully demonstrates the implementation of a mobile-based road damage detection system leveraging Edge AI technologies such as TensorFlow Lite and Teachable Machine. The system efficiently detects various types of road surface damage, including potholes, cracks, and asphalt peeling, with high accuracy and real-time processing capabilities. Specifically, the model achieved an accuracy of 95% for pothole detection and demonstrated a low average detection latency of 200 milliseconds in urban settings. The integration of lightweight CNNs optimized for mobile deployment ensures low latency and independence from cloud infrastructure, making the solution scalable and cost-effective. By providing instant feedback and facilitating proactive maintenance, this approach successfully addresses the limitations of traditional road monitoring methods while promoting safer and more efficient transportation networks.

Looking forward, several enhancements can further improve the system's effectiveness. Increasing the diversity of the training dataset by incorporating images from various geographical locations and environmental conditions can enhance the model's robustness and generalizability. Additionally, advancing the model's architecture to handle more complex and nuanced types of road damage, such as uneven surfaces or erosion, can expand its applicability. Improving model accuracy through techniques such as fine-tuning, ensemble learning, or hybrid approaches is another promising avenue. Furthermore, integrating advanced features like predictive analytics or crowdsourced data aggregation can enable more comprehensive and dynamic infrastructure monitoring. These developments will help solidify the role of mobile-based solutions in revolutionizing road condition monitoring and maintenance practices.

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