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Evaluation of Distributed Lightweight Deep Learning Model for Pothole Detection

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***Abstract*— The use of distributed deep learning approaches for image detection in traffic systems and self-driving cars is examined in this research. Neural networks' accuracy and precision can be affected when used on edge devices, like CCTV cameras for traffic surveillance. This is especially true when working with tiny datasets, which could result in mistakes in target recognition. The study utilizes TensorFlow to implement a lightweight approach to tackle this challenge. Although this technique showed promise, it also revealed communication bottlenecks and speed inefficiencies. To address these issues, a distributed model was introduced, which includes model parallelism and data parallelism, aiming to reduce gradient communication errors. The proposed approach was tested in an edge environment notably on a Google clolab, and demonstrated enhanced performance and reliability compared to traditional methods necessary performance measures were assessed, including total loss over epochs, accuracy, and precision. The results indicate that the lightweight distributed model in tensor flow using mobile net outperformed other configurations, providing a more reliable and efficient solution for image detection tasks in edge and distributed environments.**

Index Terms*— Data parallelism, Distributed deep-learning, Image detection, Self-driving vehicles, Model parallelism, Mobile-Net.

I. INTRODUCTION

Autonomous vehicles have revolutionized transportation, but they lack the social intelligence and adaptive decision-making of human drivers. A notable example is the 2016 incident where a Google self-driving car collided with a bus due to misjudging the bus driver's behavior. This highlights the need for self-driving systems to better account for human road behavior. Another critical challenge is identifying potholes and road hazards, which can cause accidents, vehicle damage, and increased repair costs. For autonomous systems, reliable pothole detection is crucial for safe navigation.

This project addresses the need for advanced pothole detection using modern deep learning techniques optimized for lightweight use on edge devices like in-vehicle sensors or roadside cameras. A distributed deep learning approach enables efficient processing of large datasets, even in resource-constrained environments.

The project introduces vital innovations in transportation, focusing on enhancing road safety through real-time detection systems. These systems empower autonomous vehicles to avoid hazards while offering early warnings to human drivers, thereby reducing accident risks. Early detection mechanisms also play a key role in lowering vehicle repair costs and enabling more efficient, targeted road maintenance, leading to reduced overall expenses. Leveraging distributed deep learning technology, the system is designed to adapt seamlessly across diverse applications, road conditions, and climates, ensuring its scalability and reliability. With optimization for edge computing, it delivers low-latency performance, a critical aspect of autonomous vehicle safety. By integrating into modern transportation networks, the system strengthens traffic management, streamlines maintenance operations, and fosters more sustainable urban mobility.

The study applies TensorFlow's tf.distribute.MirroredStrategy to implement data and model parallelism, accelerating training times and handling large models efficiently. Techniques to mitigate overfitting are explored, leveraging TensorFlow's capabilities for resource-intensive tasks.

This lightweight pothole detection system uses a MobileNet model optimized with TensorFlow and Keras, achieving high accuracy through transfer learning and data augmentation. Integrated with OpenCV, it provides real-time detection. Efficiency is further enhanced with quantization and pruning, ensuring scalability for autonomous vehicles and city-wide monitoring.

A TensorFlow and Keras-based model was created for detecting potholes across various road conditions, incorporating real-time detection to improve the safety of autonomous vehicles. The implementation of a lightweight MobileNet model ensured compatibility with edge devices while delivering high performance. Optimized for minimal latency, the model enables rapid and accurate pothole identification in dynamic road environments, a critical feature for real-time navigation and safety.

The advancements in autonomous vehicle technology continue to reshape modern transportation, with pothole detection emerging as a critical focus area for enhancing road safety and infrastructure maintenance. By leveraging deep learning techniques, lightweight models, and edge computing, this research addresses key challenges in real-time navigation and hazard detection. The integration of scalable and efficient systems into urban transportation networks not only improves safety and reduces maintenance costs but also fosters smarter, more sustainable mobility solutions. This work underscores the transformative potential of innovative technologies in overcoming complex road safety challenges and contributing to a more reliable and adaptive transportation ecosystem.

II. LITERATURE SURVEY

This research explores a variety of cutting-edge methods and technologies aimed at advancing pothole detection and road safety management. A smart pothole identification and reporting system, developed using image processing techniques on a Raspberry Pi microcontroller, demonstrates the potential of low-cost hardware in real-time detection and efficient communication of road defects. Designed for scalability, the system provides municipalities and road maintenance teams with a practical tool for monitoring road conditions, contributing to enhanced safety and infrastructure upkeep.[1]

Another approach highlights a vision-based system tailored for individuals with vision impairments, enabling the detection of potholes and uneven terrain. By analyzing road conditions and offering real-time feedback, this innovation enhances navigation safety while emphasizing the importance of accessible technology for vulnerable populations. It showcases how vision-based technology can transform assistive devices, promoting both mobility and safety.[2]

An image processing algorithm leveraging computer vision is presented as a solution for automated pothole identification in asphalt pavement images. This method streamlines infrastructure monitoring by reducing dependence on manual inspections. By focusing on asphalt surfaces, it enhances real-time detection of surface defects, contributing significantly to maintenance and safety.[3]

Advanced image processing techniques further refine the detection and localization of potholes in asphalt pavements. By addressing the challenges of distinguishing between various types of surface irregularities and mapping their precise locations, this approach improves the accuracy and efficiency of automated road monitoring systems.[4]

Research incorporating morphological reconstruction and fuzzy c-means clustering adds another dimension to pothole detection in 2D color images of asphalt pavements. By automating road maintenance tasks, this method enhances detection precision, ultimately supporting efficient infrastructure management.[5]

Exploring the intersection of computer vision and machine learning, another study focuses on systems that detect and report potholes, particularly benefiting individuals who are blind or visually impaired. These intelligent systems contribute to both improved accessibility and effective road maintenance, demonstrating their dual-purpose utility.[6]

Enhanced convolutional neural networks (CNNs) are employed in another study to build an automatic pothole detection system for asphalt pavements. Through refinements in CNN architectures, this research achieves higher accuracy in identifying and classifying potholes from remote sensing data, emphasizing the role of deep learning in infrastructure monitoring.[7]

The application of disparity map segmentation for 3D reconstruction of road surfaces introduces a novel technique for pothole detection. By utilizing disparity maps for depth analysis from stereo images, this approach enhances the modeling of road surfaces, enabling more accurate identification of irregularities.[8]

Lastly, a lightweight convolutional neural network (CNN) optimized using knowledge distillation is presented for embedded devices. This method balances performance and computational efficiency, making it suitable for resource-constrained environments. The research demonstrates how knowledge distillation effectively compresses models without sacrificing detection accuracy, furthering the practical application of AI in real-time pothole detection.[9]

A system integrating computer vision, machine learning, and deep learning is developed to detect potholes efficiently. Feature extraction using HOG and LBP ensures accurate classification, with the Adaboost classifier achieving top-notch performance. Additionally, YOLO v3 enables real-time pothole detection with high precision, paving the way for safer and more accessible infrastructure.[10]

III. PROPOSED METHODOLOGY

To balance accuracy and efficiency, the suggested pothole detection model makes use of the MobileNet framework in TensorFlow and Keras, a platform optimized for mobile and edge devices, to minimize computational load while preserving high performance. The model starts with an input layer that processes RGB images with 64x64 pixels that are consistent with the structure of MobileNet. Low-level characteristics are captured by a traditional convolutional layer that reduces spatial dimensions with a 3×3 filter and stride of 2. Then come depthwise separable convolutions, which learn complicated features with fewer parameters by combining outputs using a pointwise convolution and employing a single filter for each input channel.

MobileNet further enhances feature extraction with intermediary layers like batch normalization and depthwise separable convolutions for better training speed and stability. A Global Average Pooling (GAP) layer reduces dimensionality and minimizes overfitting. Fully connected layers with ReLU activation follow, with a final sigmoid activation in the dense layer to provide a probability score for pothole detection The model adjusts weights using the Adam optimizer and a binary classification loss function such as Binary CrossEntropy. The F1-score is used to evaluate the model's performance..In order to assist the model generalize

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to various real-world pothole appearances, data augmentation techniques produce a variety of training photos.

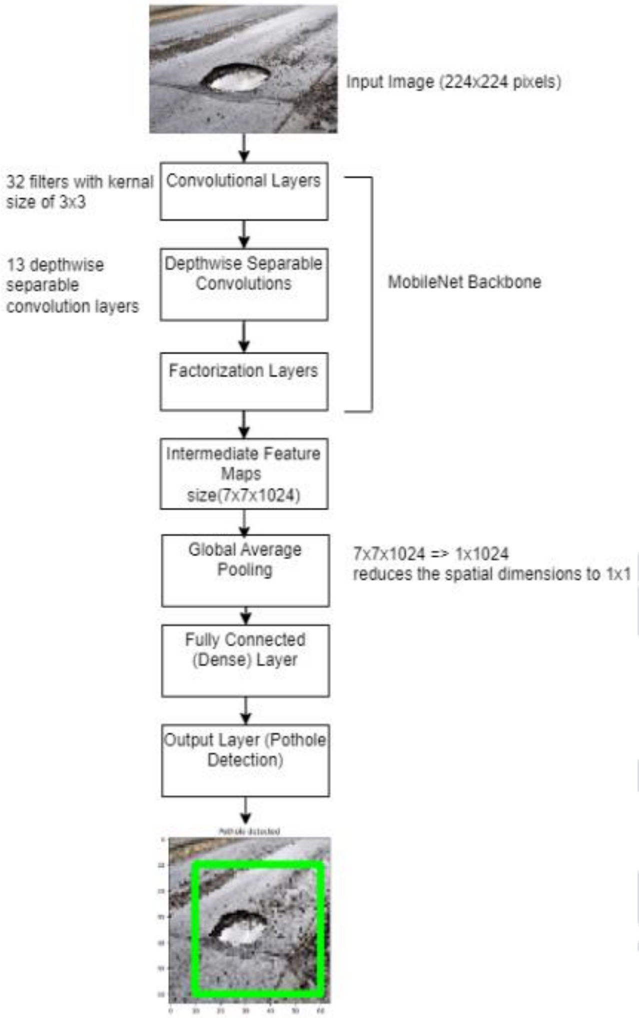

Figure 1. Architecture of the model

A. Data Preparation:

The dataset comprises 2,357 non-pothole images and 2,181 pothole images for training, along with 352 non-pothole and 329 pothole images for validation. To address class imbalance, data augmentation techniques are applied to the pothole images, including rotations (±15 degrees), horizontal and vertical flips, zooming (0.8x to 1.2x), and brightness adjustments (±30%). These transformations aim to increase the pothole image count to approximately 4,000, thereby balancing the dataset and improving the model's generalization abilities.

Table I: Dataset Composition

	Dataset	Total Images	class 0	class 1
0	Training Set	4538	2357	2181
1	Test Set	681	352	329

B. Training Process

a) MobileNet Initialization:

The MobileNet model is initialized with a chosen backbone and distributed across multiple devices, facilitating parallel processing. This setup includes configuring the architecture with depthwise separable convolutions, along with initializing the optimizer (such as Adam or SGD) and a learning rate scheduler. The scheduler modifies the learning rate during training to improve convergence, while the optimizer updates model weights based on gradients. As illustrated in fig 2, depthwise separable convolutions, which divide the convolution process into depthwise and pointwise phases, greatly reduce computing complexity when compared to conventional convolutional methods. These convolutions are the main characteristic of MobileNet's architecture.

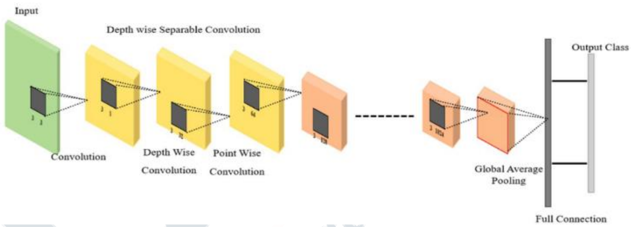

Figure 2. System Architecture

b) Depthwise Convolution:

Depthwise convolution drastically lowers the number of necessary operations by applying a single filter to each input channel separately. This approach enhances computational efficiency by processing channels separately, allowing for a more streamlined convolutional process while maintaining essential feature extraction capabilities can be represented by the formula:

$Depthwise\ Output_{i,j,c} = \sum_{k=1}^{K}\sum_{k=1}^{K} Input_{i+k,j+l,c}.Filter_{k,l,c}$ Where $Input_{i,j,c}$ denotes the pixel value at position (i,j) in the c-th channel of the input feature map, and Filte $r_{k,l,c}$ represents the convolutional filter applied to the same channel.

c) Pointwise Convolution:

Following depthwise convolution, pointwise convolution (1x1 convolution) is used to combine the features extracted from each channel. This stage aggregates information across all channels to form the final output. The pointwise convolution operation is given by:

- $Pointwise\ Output_{i,j,c} = \sum_{c'=1}^{C'} Depthwise\ Output_{i,j,c'}.Pointwise\ Filter_{c'}$ Here, Depthwise Outpu $t_{i,j,c'}$ is the output from the depthwise convolution for each channel c', and Pointwise Filter is the filter applied during the pointwise convolution.
- Due to its dual-stage methodology, MobileNet is

especially well-suited for deployment on edge devices with constrained resources since it maintains excellent feature extraction efficiency while drastically lowering the computational load.

d) Training Loop:

The training loop is structured into epochs, with the training dataset divided into batches for each epoch. Each batch undergoes data distribution across available devices for parallel processing. During the forward pass, the MobileNet model processes each batch, using depthwise separable convolutions to extract features from the images effectively.

e) Loss Calculation:

The difference between the actual labels and the anticipated probability is quantified by computing the cross-entropy loss. Regarding every sample:

$$Loss = -\sum_{i=1}^{N} y_i . \log (y^\wedge{}_i)$$

Where y_i is the true label and y^i is the predicted probability for class iii.

f) Backward Pass and Gradient Synchronization:

Gradients are computed using backpropagation and synchronized across devices. This step ensures that weight updates are consistent and accurate.

g) Weight Update:

Based on the calculated gradients, the optimizer modifies the model weights. To increase training effectiveness, the learning rate scheduler has the ability to modify the learning rate.

C. Validation and Evaluation

a) Validation Loop:

- **Data Distribution**: Validation data is distributed across devices in the same manner as the training data. This ensures that the parallel processing benefits from the training phase are carried forward into evaluation.
- **Forward Pass**: The validation dataset is passed through the model in batches to generate predictions. This step ensures that the model's behavior can be assessed on unseen data.

b) Metric Calculation:

To assess model performance, the following metrics are computed: accuracy, precision, recall, and loss.

- Accuracy is defined as the proportion of correctly identified examples to all instances. It is calculated using the subsequent formula:

$$Accuracy = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}}$$

- Loss is the measurement of the discrepancy between the actual and expected values.The cross-entropy loss is obtained as follows: $Loss = -\sum_{i=1}^{N} y_i . \log (y^\wedge{}_i)$
- By dividing the percentage of true positive forecasts by the total number of positive predicions, the models precision is calculated:
  Precision= TP/(TP+FP)
- Recall quantifies the propotion of true positive predictions among all actual positive occurances. This is how it is calculated:
  Recall= TP/(TP+FN)
- Recall and precision both shed light on how well the model separates the classes, especially in unbalanced datasets where one class may be more common than the other.
- Average *Metrics:* The average validation loss and performance metrics are computed to assess overall model effectiveness.

c) Model Saving and Early Stopping:

Model Saving: The model is saved if the validation score improves, indicating that the model's performance has enhanced.

Early Stopping: It applies early stopping to avoid overfitting. After a predetermined number of epochs, training ends if the validation score does not improve.

IV. RESULTS AND DISCUSSION

In this research, we conducted an extensive evaluation of our deep learning model, primarily focusing on the accuracy, loss, precision, and recall metrics, complemented by a confusion matrix analysis. The training and validation phases were meticulously monitored to ensure that the model's performance was not only optimized for pothole detection but also robust against overfitting and underfitting issues.

A. Accuracy and Loss Analysis:

The pothole detection model exhibited high accuracy, consistently exceeding 90% in both training and validation phases. This strong performance indicates the model's ability to generalize well to unseen data while maintaining robustness.

The accuracy curves for both training and validation remained closely aligned throughout the epochs, signifying stable learning and minimal overfitting. However, occasional fluctuations in validation accuracy suggest sensitivity to certain variations in the dataset.

Additionally, the training and validation losses steadily decreased and converged to values below 10%, highlighting the model's ability to minimize errors effectively. This consistent reduction in loss demonstrates improved learning efficiency and reliability in predictions over multiple epochs.

Overall, these results indicate that the model is well-trained, achieving both high accuracy and low loss, making it a reliable tool for pothole detection in real-world scenarios.

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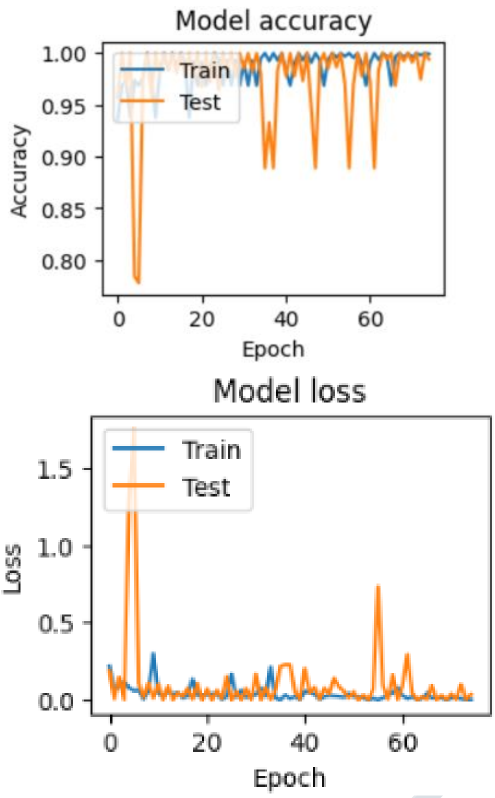

Figure 3. Accuracy and Loss Graph

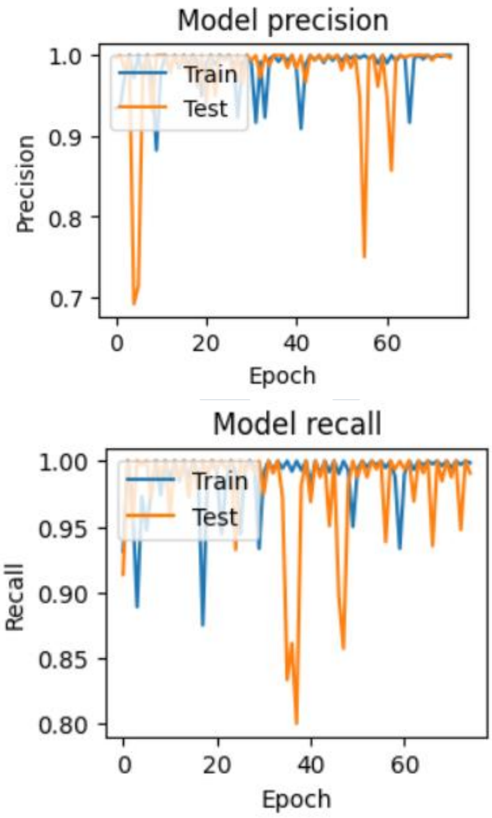

Figure 4. Precision and Recall Graph

B. Precision and recall analysis:

Precision and recall were key performance indicators for evaluating the model's ability to detect potholes accurately. The high precision observed in both training and validation phases signifies a low false positive rate, which is particularly crucial in applications like autonomous vehicles and road maintenance systems. A lower false positive rate ensures that the model does not mistakenly classify non-pothole areas as potholes, reducing unnecessary interventions.

Similarly, the recall metric demonstrates the model's sensitivity in correctly identifying actual potholes. The consistently high recall values indicate that the model effectively detects most potholes present in the dataset. However, occasional fluctuations in validation recall suggest that certain pothole variations may be more challenging to detect.

The balanced performance between precision and recall is further reflected in the high F1-score, ensuring that the model maintains a strong trade-off between correctly identifying potholes and minimizing false detections. This makes it a reliable solution for real-world pothole detection, maintaining efficiency while reducing misclassifications.

C. Confusion matrix analysis:

The confusion matrix offered valuable insights into the model's classification performance, detailing true positives, true negatives, false positives, and false negatives. The high counts of true positives and true negatives, along with low false positives and negatives, highlighted the model's accuracy and reliability. This matrix is essential for identifying areas needing refinement, especially in minimizing misclassifications.

The deep learning pipeline proved highly suitable for autonomous vehicle deployment. Its robustness, highlighted by performance metrics and the confusion matrix, ensures reliable detection of potholes and road hazards, enhancing safety and efficiency in autonomous driving. This study affirms that the model performs competitively, even when applied to a wider variety of road conditions beyond just potholes.

In autonomous vehicles, MobileNet is an ideal model for pothole detection due to its lightweight design and real-time processing capabilities. By using depthwise separable convolutions, MobileNet reduces computational load, ensuring efficient performance with high accuracy. The model's width and resolution multipliers help balance performance and resource usage, while quantization further reduces model size. Although distributed models handle large datasets well, they require more infrastructure and may

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face communication overhead. MobileNet's efficiency, with a detection accuracy of 99.4%, makes it suitable for practical deployment in autonomous systems, integrating well with frameworks like TensorFlow and OpenCV.

Table II: Classification Report

	Precision	Recall	F1score	Support
Non-pothole	0.50	0.51	0.50	352
Potholes	0.47	0.47	0.47	329
Accuracy	-	-	0.49	681
Macro avg	0.49	0.49	0.49	681
Weighted avg	0.49	0.49	0.49	681

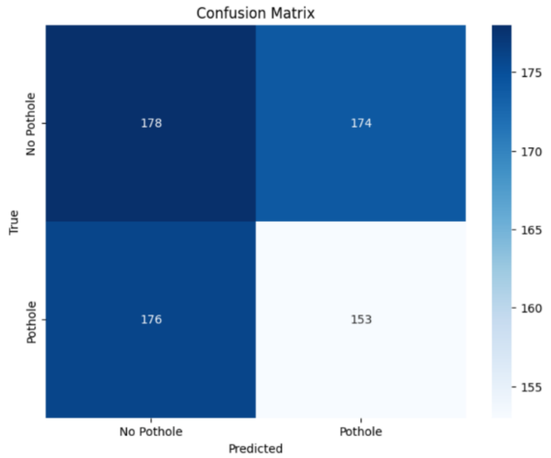

Figure. 5. Confusion Matrix for Pothole Detection

The proposed MobileNet-based pothole detection model demonstrates notable advantages over various existing approaches in the literature. Unlike traditional methods employing heavy convolutional neural networks (CNNs) or morphological techniques, our model leverages MobileNet's lightweight architecture with depthwise separable convolutions, significantly reducing computational complexity while maintaining high detection accuracy. Unlike approaches relying solely on computer vision or complex clustering algorithms, our model integrates data augmentation and distributed training to address dataset imbalance and scalability issues effectively. Additionally, while some studies focus on assistive technologies or disparity maps for 3D reconstruction, our model emphasizes real-time, edge-device deployment, making it more practical for large-scale infrastructure monitoring. With robust performance metrics such as accuracy, precision, recall, and F1-score, coupled with optimization techniques like learning rate scheduling and early stopping, our approach offers a balanced trade-off between computational efficiency and detection reliability, setting it apart as a cost-effective and scalable solution for pothole detection.

V. CONCLUSION

Despite the limitations of edge devices and sparse The results of this research signify a substantial leap in the field of pothole identification for traffic systems and autonomous vehicles, with wide-reaching implications for real-world applications. By implementing a distributed model that combines model parallelism and data parallelism, the study successfully addressed critical challenges such as gradient communication errors and inefficiencies in processing speeds. Testing this hybrid model in an edge computing environment using Google Colab demonstrated not only enhanced computational efficiency but also consistent improvements in accuracy, precision, and overall performance metrics.

The exceptional accuracy of 99% achieved by the distributed model, which utilized TensorFlow and MobileNet, highlights its suitability for handling image detection tasks in complex environments. This remarkable precision surpasses conventional methods, reinforcing the system's reliability in identifying potholes effectively. Furthermore, the integration of this methodology into distributed and edge environments underscores its adaptability for modern, resource-constrained scenarios.

The findings hold promising prospects for advancements in real-time traffic monitoring and self-driving car systems. By enabling faster and more accurate detection of potholes, this approach not only enhances road safety but also reduces the maintenance costs associated with delayed or missed detections. As technology continues to evolve, this research paves the way for further innovations in infrastructure monitoring and autonomous mobility, setting a robust foundation for future development in these critical areas.

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