AI-Driven Road Damage Detection in the Philippines: Leveraging SSD and Crowdsourced Data for Infrastructure Evaluation

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Abstract

This research proposes an innovative AI-driven road damage detection system specifically designed for the Philippines, addressing the pressing issue of road safety exacerbated by deteriorating infrastructure. Utilizing crowdsourced data, the system employs advanced algorithms, particularly the Single Shot Multibox Detector (SSD), to analyze user-submitted images of road conditions. The study highlights the significant correlation between poor road conditions and increased traffic accidents, particularly among young Filipinos, and emphasizes the potential of artificial intelligence in enhancing real-time monitoring and repair processes. Initial testing using the RDD2022 dataset shows moderate success in detecting road cracks, indicating room for improvement in model accuracy and inference speed. Future work will focus on optimizing model performance and expanding localized datasets to enhance detection capabilities, generate valuable insights for the Department of Public Works and Highways (DPWH), to facilitate informed decision-making regarding maintenance priorities and resource allocation and contribute to safer road networks in the Philippines.

Keywords: AI-Driven Road Evaluation, Damage Detection, Road Infrastructure, Quality Control, SSD

1. Introduction

Road safety is one of the most vital parts of every country's daily economic growth. By prioritizing it, countries can reduce accidents, fatalities, and injuries, thereby minimizing healthcare costs and productivity losses [1]. However, despite the advancements, road traffic accidents remain a significant public health issue, particularly in developing countries [2]. According to the Philippine Statistics Authority (PSA), road traffic deaths surged by 39% from 2011 to 2021, with traffic injuries being the leading cause of death among Filipinos aged 15-29, as well as child mortality [3].

Numerous studies [5]-[10] have demonstrated a strong correlation between road surface conditions and traffic accident rates. It was proven that poor road conditions, characterized by large potholes and deep cracks, can significantly increase the risk of severe accidents, especially on high-speed roads, involving both single-vehicle and multi-vehicle collisions [4].

The utilization of artificial intelligence in efficiently detecting and repairing road damages holds the potential to significantly reduce accidents, thereby streamlining the repair process and enhancing cost-effectiveness. Machine learning techniques, particularly the application of convolutional neural networks (CNNs), have proven to be highly effective in accurately and efficiently detecting various road faults. In the field of motor fault detection, [15] and in road fault detection, [16], both substantiate the real-time monitoring capabilities of CNNs. Further research [13] has demonstrated the effectiveness of CNNs for real-time road detection, even with large contextual windows. Collectively, these studies strongly support the use of CNNs for accurate and timely road fault identification.

Moreover, market data by Newzoo said the Philippines has almost 70 million smartphone users [3]. This suggests the feasibility of leveraging crowdsourced image data from Filipino citizens to enhance algorithmic performance. This approach also enables the generation of a scalable damage map based on the geospatial distribution of crowdsourced information.

2. Background and Related Works

2.1 AI in Road Infrastructure

The utilization of artificial intelligence in efficiently detecting and repairing road damages holds the potential to significantly reduce accidents, thereby streamlining the repair process and enhancing cost-effectiveness. Researchers have developed numerous methods [14] - [16] to track road conditions, and each approach possesses its own set of advantages and disadvantages. Some methods for tracking road conditions using artificial intelligence include unsupervised learning, bus trajectory analysis, integration of smart sensors and machine learning, cameras installed on cars, and deep learning. Identifying the most suitable approach can be achieved through a discerning consideration of subtle distinctions inherent in each technique.

2.2 Convolutional Neural Networks (CNNs)

Smart sensors and machine learning analyze data from a network of sensors using conventional machine learning techniques, providing high accuracy and a wide range of defect detection capabilities [14]. However, using this strategy can be expensive and time-consuming because it requires a lot of training and data collection. Convolutional neural networks (CNNs) are used by deep learning and vehicle-mounted cameras to interpret images that are taken by cameras placed on cars [15]. This approach makes use of the current vehicle infrastructure while providing quicker processing rates and more effective operation. Its accuracy is restricted to flaws that are visible in the photos that were taken, e.g. flaws that are hidden by reflections or shadows may be difficult for it to detect. Bus trajectory analysis and unsupervised learning use unsupervised learning algorithms like k-means clustering to find patterns in bus trajectories that differ from typical behavior and could be signs of possible road issues [16]. Because it uses current GPS data from buses without requiring extra infrastructure, this solution is both scalable and cost-effective. Its accuracy is not as high as that of the other approaches, though, and it takes some effort to distinguish between other factors and road problems when interpreting trajectory patterns.

2.3 Related Works

The system's particular needs will determine which algorithm is best; as needed, accuracy, efficiency, cost, and fault range will be given priority. Machine learning methods, particularly convolutional neural networks (CNNs), have been shown to be effective in detecting a variety of road faults with high accuracy and efficiency. [11] and [12] both demonstrate the real-time monitoring capabilities of CNNs in motor fault detection and road fault detection, respectively. [13] further highlight the efficiency of CNNs in road detection, with Mendes focusing on a large contextual window and real-time inference. These studies collectively support the use of CNNs for efficient and accurate detection of road faults. The advancement of smartphone cameras has made crowdsourcing a viable option for collecting image data, as it can significantly reduce costs. [17] propose energy-efficient crowdsourcing systems that exploit smartphone app opportunities and quantify the quality of crowdsourced photos, respectively. Zhang [18] introduces a privacy-friendly image dataset purchasing framework, which could further reduce costs by leveraging available mobile users. Finally, Chen [19] focuses on improving outdoor crowdsourcing photo collection on smartphones, which could enhance the efficiency of image data collection. These studies collectively highlight the potential of smartphone-based crowdsourcing for image data collection.

3. Proposed Work

In response to the growing challenges of deteriorating road infrastructure in the

Philippines, this research presents a framework for an AI-driven road damage detection system that integrates crowdsourced data for real-time infrastructure evaluation. The system employs advanced AI algorithms, particularly the Single Shot Multibox Detector (SSD), to analyze images submitted by users, providing a quantitative assessment of road quality on a scale from 0 (severely damaged) to 5 (excellent condition). This innovative approach empowers citizens to actively participate in monitoring road conditions while generating valuable, real-time data that is often missing in traditional infrastructure assessments.

3.1 Registration and Image Upload

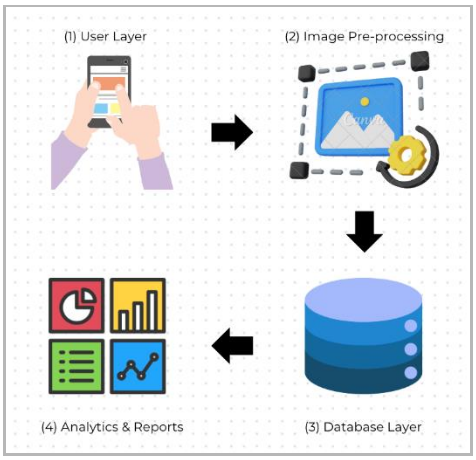

Figure 1. Data Flow Diagram

The process begins with users registering on the mobile app or web interface, where they provide essential information about their location and upload images of road conditions. The system captures metadata such as:

- Location coordinates
- Date and time of upload
- User identification (optional)

Once an image is uploaded, it enters the Data Processing Layer for analysis.

3.2 Data Processing

The uploaded images undergo several processing steps to enhance detection accuracy. First, image pre-processing is performed to improve the quality of the input for better detection results. The Single Shot Multibox Detector (SSD) is then applied to identify road damage features, such as cracks or potholes. The model is trained on the RDD2022 United States dataset, which includes annotated images of various road damage types, and is tested using a Philippine road crack image to assess its performance on local infrastructure. The results of the detection, along with relevant metadata, are then stored in the Database Layer for further analysis and reporting.

3.3 Analytics and Reporting

The processed data is analyzed to generate reports that visualize road conditions across different areas. Stakeholders can access this information through a dashboard that displays key metrics such as average road quality scores, areas requiring urgent maintenance, and trends over time based on user submissions.

The data generated through this system will be highly beneficial for the Department of Public Works and Highways (DPWH), as it will provide valuable insights into road conditions across various regions. By leveraging this information, the DPWH can make informed decisions regarding maintenance priorities, resource allocation, and infrastructure improvements, ultimately enhancing the safety and quality of public roads.

4. Testing and Results

4.1 Dataset Description

For evaluation, we used the RDD2022 United States dataset, which includes annotated images of road damages such as cracks and potholes, with corresponding condition labels. This dataset contains a diverse range of road damage types and is widely used for road damage detection tasks. For testing purposes, we selected a Philippine road crack image as an example to assess how the model performs in detecting road cracks specific to the context of the Philippines.

4.2 Experiment Setup

- Hardware: The testing was conducted on a MacBook Pro with Apple Silicon M1.

We utilized Google Colab with GPU acceleration to optimize model performance during inference.
- Libraries and Frameworks: The system relies on TensorFlow to implement the Single Shot Multibox Detector (SSD) for road damage detection. Other libraries such as OpenCV were used for image preprocessing and visualization, while NumPy was used for array manipulations and processing.

4.3 Prototype Testing

Figure 2. Interface

The SSD model was evaluated on the Philippine Road Crack Image, with a focus on detecting road cracks. The inference results from the SSD model were analyzed to assess how well the model generalized from the United States dataset to a real-world road image from the Philippines.

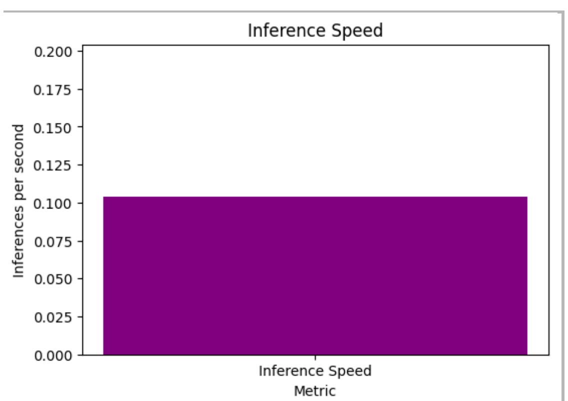

Figure 3. Inference Histogram

Inference Metrics:

- Inference Time: 9.60 seconds
- Inference Speed: 0.1042 inferences per second
- Detection Information: Class 5 (road crack) with a detection score of 0.6302.

The inference time of 9.60 seconds shows that the SSD model processes the test image in a reasonable amount of time, making it suitable for moderate real-time applications. The inference speed of 0.1042 inferences per second suggests the model operates at a moderate pace, which can be optimized further for real-time applications with hardware acceleration. The detection score of 0.6302 indicates a moderate confidence level for the detected road crack (Class 5). This suggests that the model can detect cracks with a reasonable degree of certainty, though further training or tuning might be required for higher confidence.

5. Conclusion and Future Works

This research demonstrates the potential of the Single Shot Multibox Detector (SSD) in road damage detection, particularly in the context of the Philippines. Using the RDD2022 United States dataset for model training, we applied the SSD model to detect road cracks in a Philippine road image. While the model was able to successfully identify road cracks, the detection score of 0.6302 indicates that the model's confidence in identifying cracks was moderate. This points to an opportunity for improvement in terms of accuracy and reliability, especially for practical applications in real-world environments.

The relatively low detection score highlights several areas for enhancement. One key limitation is the lack of a comprehensive Philippine-specific road damage dataset. Since the SSD model was primarily trained on the RDD2022 dataset, which contains road damage types from the United States, its generalization to local road conditions, such as the unique characteristics of Philippine roads, remains an ongoing challenge. The absence of more localized data can result in reduced performance when the model is applied to images outside the training dataset, especially for features that may not be well-represented or are different in the Philippine context.

Another area for improvement is optimizing the model's inference speed and detection confidence. While the current model performs adequately in terms of inference time, there is room for further optimization, especially with hardware acceleration and model fine-tuning. Future research will explore faster model architectures or methods such as model pruning to reduce computational demands while maintaining detection accuracy.

Finally, real-time road monitoring through the integration of crowdsourced data will be an essential next step. By enabling citizens to actively contribute to the detection of road damage through their mobile devices, the system can continuously gather fresh data to improve the model over time. Additionally, creating a seamless platform for the collection, processing, and analysis of road damage images will provide valuable insights for urban planning and infrastructure maintenance, ultimately contributing to more sustainable and safer road networks in the Philippines.

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