Real-Time Road Condition Detection and Mapping Using YOLOv11 and Built-In Car Dashcam

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Abstract

Road surface conditions decline due to heavy traffic, severe weather, and recurring utility works. Many road agencies still rely on manual windshield surveys and semi-automated inspections. These methods are time-consuming, difficult to scale, and labour-intensive. Advances in deep learning and the widespread availability of vehicle dashcams now offer new opportunities for low-cost, automated pavement assessments. This contribution presents a mobile, dashcam-based framework for detecting road-surface defects using the latest YOLOv11. This model is combined with geolocation tagging for spatial visualization. To test our YOLOv11 training model, we initially created a dataset at the University of the Fraser Valley campus. We manually annotated the dataset to identify crack fillings, crosswalk markings, speed bumps, lane markings, and other surface conditions. This was a prototype, with the aim of later training it to detect all road conditions, such as gravel, potholes, and uneven roads. To address variations in lighting and motion, augmentation techniques were applied. YOLOv11 achieved a mean average precision above 90% across all tested categories. This prototype demonstrates a practical, low-cost approach for real-time pavement monitoring. Future work includes expanding data collection, developing an operational dashboard for authorities, pinpointing exact GPS coordinates on maps with damaged road images, and evaluating model performance across different data sources, including models trained using Google Images. By producing actionable geospatial information, this system enables more efficient maintenance workflows. It provides a scalable pathway for municipalities seeking to modernize their road-condition assessments.

1. Introduction

Road surface conditions are increasingly compromised by rising traffic volumes, harsh weather patterns, and repeated utility maintenance (Maeda et al., 2018). To evaluate pavement conditions, road authorities still rely heavily on windshield surveys, visual assessments conducted from within a moving vehicle, and semi-automated inspections. These approaches are labour-intensive, time-consuming, and often costly to scale. Recent advances in computer vision and machine learning offer an efficient alternative (Fan et al., 2020). With the growing availability of in-vehicle cameras, inexpensive dashcams, and lightweight deep learning models such as the latest You Only Look Once (YOLOv11) architecture, road distress detection can be performed rapidly, safely, and at significantly lower cost.

Recent works have shown the feasibility of image-based distress detection using mobile platforms. Barbieri and Lou (2024) utilized YOLOv5 with fixed-mounted vehicle cameras and GPS sensors to identify multiple types of pavement distress. Although their system produced strong segmentation results, it relied on limited GPS capabilities and non-optimized hardware. Ranyal et al. (2022) and other researchers used smartphone imagery with object detection models to identify cracks and potholes, demonstrating promising early-stage accuracy. However, their approaches required controlled lighting conditions and lacked robust geolocation tagging.

While these studies demonstrate the effectiveness of deep learning for pavement inspection, several shared limitations remain prominent: sensitivity to lighting conditions, inadequate or unstable geolocation systems, and the absence of true end-to-end workflows that transform detections into spatially explicit, map-based outputs. In particular, the real-time mapping and visualization of detected road defects, which are crucial for operational maintenance and decision-making support, are largely missing from existing implementations.

This study aims to address these gaps by leveraging low-cost vehicle dashcams and state-of-the-art YOLO models to develop a fast, accurate, and inexpensive framework for road distress detection and geospatial visualization.

2. Related Work

There have been a few studies conducted regarding road conditions. The one that closely relates to this project is a study conducted by Ranyal et al. (2022), where they used a vibration-based system, smartphone sensors, and vision-based AI. All these are great ways to determine road condition but lack full functionality. For example, vibration-based systems are a great way to determine road surfaces. However, unless noise filtering is used, the system would be sensitive to noise. The other ideologies discussed are all innovative but also fragmented since they would mostly only cover the vehicle's wheel path, rather than the whole road, or struggle with environmental variability.

Another paper by Sattar et al. (2018) focused on smartphone-based road surface detection. This study, also doable, has several limitations since smartphone-based detection relies on gyroscope data and accelerometer data.

This method has a low accuracy rate due to low sampling frequencies, vehicle suspension systems, and driving behaviour.

In contrast to the smartphone-based systems and the vibration-based method, the dashcam-based approach is more reliable and consistent. It doesn’t rely on vibrations. Dashcam-based approach relies on visual data and makes decisions based on the trained model. It gives more accurate results, covers the whole road surface, and works well regardless of vehicle speed. The studies conducted by Ranyal et al. (2022) and Sattar et al. (2018) explore unique approaches but struggle with noise sensitivity or environmental variability. They lack the balance between cost, efficiency, and accuracy. The dashcam-based approach is more accurate and continues to improve the more the model gets trained and has minimal to no cost either. As for the data processing, there are settings like data augmentation and geospatial integration that can be changed to make the model work better regardless of brightness, bumpiness of the road, or noise levels. Like other studies, this one also has its flaws and areas that need improvement, such as working under extreme weather conditions and GNSS precision.

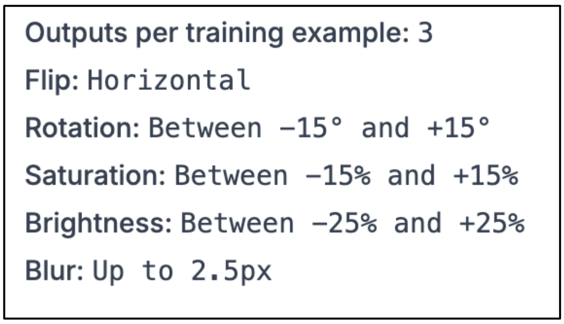

Figure 1: These are the data augmentations that were used in the dashcam-based system in Roboflow to ensure accurate results.

3. Methodology

Data Collection

Our initial testing dataset was collected from roads within our University of the Fraser Valley (UFV) campus to evaluate the performance of the prototype. To further assess model robustness, we plan to expand data collection using diverse car dashcam footage captured under varying weather and lighting conditions, enabling us to determine whether the model can consistently maintain a confidence level of approximately 90%. From the campus dashcam recordings, we extracted individual frames and manually annotated multiple road-surface features, including crack fillings, potholes, crosswalks, lane markings, speed bumps, and other relevant conditions.

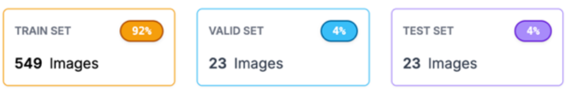

Figure 2: The dataset of 549 images was split into 3 categories: train set, validation set, and test set.

Road Surfaces

The prime focus of this research is to detect road conditions like:

1. Potholes
2. Alligator cracks
3. Crack fillings
4. Crosswalks
5. Speedbumps
6. Gravel
7. Uneven road
8. Patchwork on roads
9. Manholes

Data Augmentation

To address dashcam image variability, we adapted our augmentation method. We used controlled blur, brightness adjustments, and rotational transformations. These ensure such variations do not compromise model performance. The full dataset was pre-processed and managed within Roboflow. We also used Roboflow to train the YOLOv11 model. Figure 1 displays the augmentation used for this prototype.

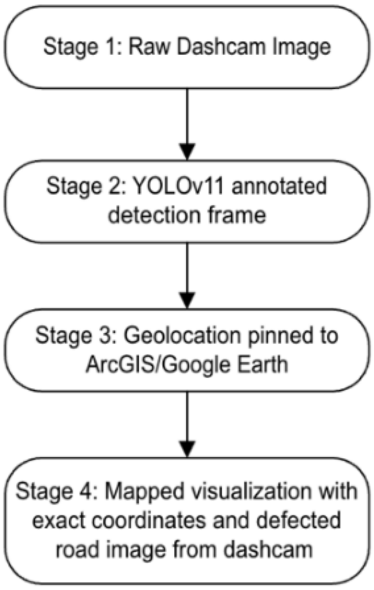

Figure 3: Four-stage processing pipeline on how to transform raw dashcam imagery to YOLOv11 detection, GPS geolocation tagging, and final mapped visualization

Geospatial Positioning

The dashcam recordings come with the exact GPS coordinates, date, and time. As the dashcam recording is played, it also displays the exact coordinates and location of the vehicles; the GNSS data is extracted from the dashcam recordings, alone with the object detected. To ensure accurate results and detections, orthorectification were also applied. This ensures spatial accuracy and correct perspective distortion. The coordinates can have a margin of error of ± a few meters, but it is sufficient to alert municipalities about road damage.

Alligator cracks **Patch** **Traffic Lines** **Gravel** **Pothole** **Speed Bump**

Figure 4: Types of road conditions trained for YOLOv11 for the project. These images were taken by the author at Janzen Street, Abbotsford, B.C.

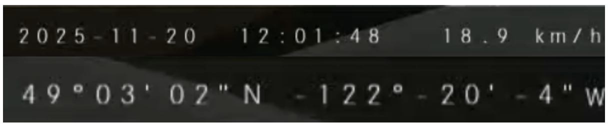

Figure 5: This is displayed under the author’s car dashcam recordings, showing exact date, time, and GPS coordinates.

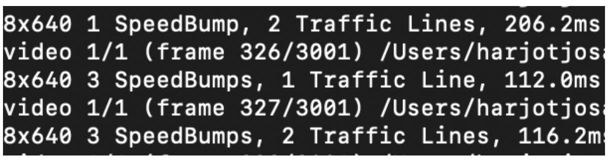

Figure 6: Gives real-time updates per millisecond on whether the YOLOv11 model detected any road condition or not. If there is nothing, it will show “no detection,” but when it detects a road condition, it will display the condition type, such as “Speed Bump." (Screenshot taken by author while testing model)

Data Scope

The data set for the prototype was collected from a Mercedes-Benz dashcam recording. If the prototype worked out so well, with a bigger data set trained, the YOLOv11 model will produce even more accurate results.

Future Work

This prototype is an example of how we can implement smart cars and municipality vehicles like garbage trucks to do a favour to the roadworks department. Garbage trucks drive around the city every week collecting garbage. If municipalities install a dashcam in the range of $150.00 - $200.00 (if not already installed), it will surplus and return the favour to them. Not only garbage trucks but also new car models and smart cars that have great dashcam quality can also help cities out. Any vehicle with a dashcam can use the YOLOv11 model to help detect road conditions and it will automatically upload any damaged road conditions to a dashboard. The dashboard will have a Google Earth integration where the areas are colour coordinates with:

1. Red: bad road condition; needs urgent care
2. Yellow: Not good, not bad road; not too urgent
3. Green: the road is good; no work needed

Besides the Google Earth integration, the dashboard will also have a real-time update where it will be updated if any bad road condition is detected by garbage trucks (or smart cars when implemented in the future). Moreover, the dashcam would talk picture automatically of the damaged road and upload it to the dashboard.

This project implementation in every city will be a benefit to them and save them thousands of dollars every year. Maintaining good road conditions is a city’s responsibility. If poor maintenance of roads results in an individual getting a flat car tire, the city is responsible for the repair due to their negligence. “You can file a claim with a municipality, city, or government and go to court at the same time” (CAA Québec, 2024). Therefore, this will save cities from unwanted claims by getting reported immediately about any damaged road that needs urgent care.

The dashboard will be available to municipalities where they can:

- View live updates
- Filter to see only one type of road condition (e.g., potholes)
- Displays the top 5 places in the city that need urgent care
- Allow people to upload pictures of damaged roads with the location
- Will update and refresh itself if new data is added
- Tell the estimated cost of repair

This is one of many ways we can use dashcams to help cities maintain safe roads. We can also install a thermal camera on garbage trucks during winter, so it can help detect black ice build-up early on. This is crucial in winters to avoid any injuries and accidents in wintertime when there is a lot of black ice buildups on roads and sidewalks. Cities will be able to spray black salt on those areas prior to ice buildups, reducing injuries and accidents by up to 80% due to early detection.

Figure 7: YOLOv11 used to detect road conditions at the UFV campus, showing a high confidence level (above 90%) on the tested conditions. The screenshots were taken from the author's running dashcam footage, showing output of the YOLOv11 model trained.

Figure 8: A thermal camera can help detect black ice ahead and potential buildups the night before (*Black Ice Detection Technology | Intelligent Vision Systems, n.d.*).

4. Results

The preliminary evaluation indicates that YOLOv11 achieved a mean average precision greater than 90% across all tested defect categories. Figure 3 presents the confidence scores for each type of detected road condition. Our tests show that even as lighting levels decreased, the model's performance remained stable, consistently producing accurate detections. The raw screenshots from our trial illustrate the full operational pipeline of the prototype and highlight key differences between our approach and previous work in this domain.

5. Discussion

Overview

The results presented here represent only a portion of our broader vision. Future work will involve developing a user interface that enables road authorities to access a geospatial dashboard, integrated with Google Earth, containing pinned locations of detected road defects for inspection and informed decision-making. Additionally, we plan to expand the model to detect other road conditions, as illustrated in Figure 2. A comparative study will also be conducted to examine performance differences between models trained on dashcam footage and those trained on Google Images. This involves training a separate YOLOv11 model on Google Image datasets and evaluating how its outputs differ from detections generated using raw dashcam recordings.

A key distinction of our research is its focus on producing actionable spatial information. By doing so, our system can be readily integrated into municipal workflows, enabling cities to prioritize repairs and improve maintenance efficiency. With the appropriate equipment and sufficient time, the system can be deployed alongside road maintenance teams to scan and assess road conditions in real-time, automatically generating live updates and georeferenced pins on Google Earth, complete with associated imagery. While this capability extends beyond the current project timeline, it represents a promising direction for future expansion and practical deployment across municipalities in Canada.

Challenges

One of the main challenges faced when collecting data was finding a car with a clean and clear dashcam. The Mercedes-Benz has a pre-installed dashcam and was easier to access than the Ford Pickup, which had a dashcam installed from a third party for $150.00. When comparing Figure 9 to Figure 10, there is a prominent difference between them since Figure 10 is more detailed and shows the dark cracks on the road, which aren't visible in Figure 9.

Figure 9: Viidure- Dashcam camera quality that was installed from a third party for less than $150.00.

Figure 10: Mercedez Benz built in dashcam has better quality and shows more detail comparatively to the third-party installer camera.

It was easier to extract dashcam recordings from the Mercedes-Benz as compared to the Ford-150 dashcam. One took me less than 2minutes while the other took more than an hour to get everything downloaded and transferred. Besides that, training the YOLOv11 model was time-consuming and required precision to ensure accuracy when the model was put to the test. Precision is necessary when training a model- every detail counts and helps make a model that is reliable and accurate.

Strengths

The more prominent feature of having a dashcam-based road condition detection is how accurate and low-cost it is. It delivers real-time updates and uploads the GPS coordinates along with an image of the damaged road to the dashboard, where municipalities have access to the data. They can view the image and determine if it needs urgent care or not. Besides that, this project delivers accurate results with up to 90% or more accuracy in road condition detection. Besides that, the system is scalable and open to change and upgrades. For this prototype, we used the YOLOv11 model and Roboflow to train the model since it was free. However, there are many advanced platforms that could build a stronger model to ensure up to 98% accuracy, but they are paid for.

Limitations

Although we had a successful prototype with a high confidence level, there were some limitations of the project. Some include:

1. Not tested in any other weather condition, like rain or snow
2. Only created a dataset consisting of daytime images, and nothing for nighttime. This could be a problem in winter since it is dark sometimes when the garbage trucks come, not being able to capture the road conditions properly
3. Not 100% accurate GNSS results, and could have potential errors as well

Achievements

Compared to previous research done, our research is more practical and accurate. Previous research focused on smartphone-based systems and vibration sensor-based methods. However, vibration sensor-based systems "generate unstable results at a low accuracy because the received amplitude vibration is influenced by the vehicle's suspension system and travelling speed" (Cao et al., 2020). Contrarily, we made a working prototype with a small dataset, and it gave us up to 90% confidence level. Therefore, training a model with a higher dataset of about 3000 images would result in even more accurate results with more road conditions. Besides that, this project had a end to end pipelining and helps municipalities by creating a dashboard for them where they can easily access the city map and the damaged roads. Dashcam-based road detection system is practical, working, and does real-time mapping. It detects road conditions in real time and updates it on the dashboard for city authorities to look at. The best feature is how It pinpoints the exact location with an image of the damaged road to see how damaged it really is. It also makes a coloured map to show what percentage of the city's roads needs work.

Remote Sensing

This method focuses more on street-level details that satellite imagery cannot cover. Satellites can't cover details like potholes, cracks, and uneven roads. Therefore, the dashcam-based system is more detailed and covers what satellite imagery cannot by collecting high-resolution data from normal vehicles and garbage truck dashcams as they drive around the city. This is an affordable yet accurate system for cities that combine dashcam footages with GPS coordinates, creating a real time road condition monitor system for everyday use and data collection.

6. Conclusion

By integrating YOLOv11 with homograph-driven orthorectification, our system can transform everyday dashcam footage into accurate, scale-aware road-condition data, complete with precise map coordinates of detected defects. This approach offers a cost-efficient, wide-coverage solution while maintaining an accuracy level of approximately 90%. Compared to previous studies, our method offers expanded functionality and is designed for seamless integration into municipal construction and maintenance workflows. It supports greater automation, real-time updates, and geospatial mapping with exact GPS references.

Figure 11: More images from the author’s prototype where the YOLOv11 model has high confidence levels. This is from the UFV campus and parking lot. (Screenshots taken by author from the car dashcam footage using the system developed)

This methodology enables reliable and scalable quantification of diverse road conditions with minimal additional cost. Moreover, the system can interface with existing GPS infrastructure and maintenance management tools, providing cities with an affordable, accurate, and scalable means to monitor and manage their road networks more effectively.

The dashcam road detection system is the future. It uses raw data to determine road conditions and tags its geographic coordinates if any detection is made on the dashboard. This smart system would go through dashcam footage in real time and update the dashboard in real time. The best part is how it also uploads an image of the damaged road with its exact GPS coordinates. The dashcam system informs us about the category of the damaged road, gives us a confidence level, and the time of detection. All these features would benefit cities by assisting them with road repairs, identifying road patterns, and pinpointing where the majority of problems are occurring. Overall, the system is reliable, precise, and efficient- especially for the future.

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