An Automated Method for Pavement Surface Distress Evaluation

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Abstract

Evaluation of surface distress is an important aspect of pavement management. The most common practice to assess surface distress is to develop a pavement condition index (PCI), with ASTM-PCI being the most widely used in evaluating flexible pavements. Traditional PCI evaluation methods rely on labour-intensive, manual inspections, leading to significant time consumption. In recent years, real-time visualization and crowdsourcing have been explored, but their potential has yet to be fully realized. Integrating real-time visualization through GIS technology offers immediate insights into pavement conditions, aiding prompt decision-making. Crowdsourcing allows a broader community to contribute to condition reporting, enhancing data accuracy and coverage. This study aims to develop an artificial intelligence (AI)--based method for road condition assessment from crowd-sourced images. A deep-learning object detection model is utilized for precise crack detection and classification. The model is trained to recognize various distress types accurately and quantify attributes crucial for determining the PCI. The developed model is then integrated into a web-based platform accessible through mobile phones and dash cameras, allowing real-time capture and classification of cracks. The study demonstrates that the automated methodology significantly enhances PCI estimation efficiency, with a high correlation between semi-automated and automated methods. Stakeholders can benefit from deep learning and automation in pavement distress detection, aiding informed decision-making through crowdsourcing data. Future work includes the detection of subclasses within crack types based on severity and the creation of digital twins for public assets. Overall, this study highlights the transformative potential of AI and crowdsourcing in improving pavement management.

1. Introduction

Optimal road conditions are crucial in ensuring safe driving and smooth traffic flow. Any degradation in road conditions affects the quality and functionality of roads, resulting in a substantial decline in traffic safety. Road segments often exhibit various surface defects, including loss of coarse aggregates, ravelling, segregation, potholes, and flushing, alongside permanent deformations like rippling, shoving, wheel track rutting, and distortions. Further, cracking issues manifest in diverse forms, including longitudinal wheel track, centre line, pavement edge, traverse, longitudinal meander, mid-lane, map, and alligator cracks.

Road infrastructure assessment and maintenance play an important role in ensuring users' secure and efficient transportation. A primary task within a pavement management system is determining the sections and roads within a network that necessitate preservation, maintenance, or rehabilitation based on their condition. The condition assessment includes many aspects, such as surface distress, surface roughness, surface friction, and structural capacity, where surface distress is the most used. Surface distress on road networks is assessed by assigning a Pavement Condition Index (PCI) as an indicator of the current state of the pavement section. Surface distress identification, severity categorization, and extent/density quantification are the three major inputs for PCI evaluation. Different methods are used to estimate the PCI values once these parameters are obtained. The ASTM PCI method is one such method that is widely used for evaluating flexible pavement conditions. However, the traditional approach entails manual PCI interpretation through field observations and calculations. This method is time-consuming and inherently subjective, susceptible to human errors. This study aims to develop an innovative approach using artificial intelligence (AI) to facilitate automated assessment of pavement surface conditions. The goal is to overcome the limitations of manual interpretation by leveraging AI technologies to streamline and enhance the accuracy of pavement condition assessments.

The evolution of computer vision technologies has facilitated the application of diverse deep-learning methods for crack detection. These techniques typically fall within two broad categories: object detection and semantic segmentation. Recent research has highlighted the utilization of various deep-learning models in this domain. Noteworthy contributions include the adoption of Convolutional Neural Network (CNN), You Only Look Once versions 3, 4, and 5 (YOLOv3, YOLOv4, and YOLOv5) for object detection (Bochkovskiy et al., 2020; Nguyen et al., 2021; Zhu et al., 2022). Moreover, crack segmentation techniques have been developed leveraging architectures such as Recurrent Adaptive Networks, UNet, DMA Net, and ECSNet (Di Benedetto et al., 2023; Liu & Wang, 2022; Qi et al., 2023; Sun et al., 2022; Zhang et al., 2023; Zhang et al., 2022; Zhang & Zhang, 2023). The refined training of these algorithms has enabled the classification of diverse forms of surface distress. Integrating these AI-driven deep learning methodologies with equation-based Pavement Condition Index (PCI) estimation presents a promising avenue, offering the prospect of devising an automated approach for advanced PCI estimation. This integrated approach holds significant potential to enhance the efficiency and accuracy of pavement condition assessments, substantially reducing both time and labour costs.

An inherent challenge in object detection lies in the requirement for sophisticated technologies for data acquisition. Conventionally, pavement data collection necessitates aerial surveys conducted through Unmanned Aerial Vehicles (UAVs) or terrestrial surveys, methodologies that often entail substantial initial capital investments. However, this study proposes to overcome this challenge using imagery sourced from freely

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accessible public platforms like Google Maps APIs. This approach enables access to crack information captured worldwide, leveraging the extensive coverage of locations available within Google Maps' Street view images. Subsequent iterations aim to implement this automated model based on inputs from devices such as Closed-Circuit Television (CCTV) cameras and dashcams. This expansion in data collection infrastructure holds the potential to enhance the breadth of data input and, consequently, improve the model's accuracy. By diversifying the sources of data collection and integrating automated detection systems into commonly used devices, this approach seeks to expand the scope of data acquisition while augmenting the model's precision and scalability.

This study adopts a Convolutional Neural Network (CNN)-based object detection model employing the YOLOv5 algorithm to identify pavement distress and diverse distress types. The model integrates semi-automated and equation-based automated PCI estimation approaches to derive the Pavement Condition Index (PCI) rating within the study area. Initially, the manual PCI estimation method is employed as a benchmark for comparative analysis, serving as the foundational aspect of this research endeavour. This comparison aims to discern the efficacy of the automated model in contrast to other methodologies utilized and identifies avenues for enhancing the accuracy and reliability of the model. The developed model is further complemented by integration into a Geographic Information System (GIS) platform, enhancing visualization capabilities. The subsequent session discusses the study area, data used, methodology, and implementation specifics of the present study.

2. Study Area

The case study is performed on Mutual Street, between Dundas Street East and Queen Street East in Downtown Toronto (Figure 1). This pavement exhibits multiple forms of deterioration, encompassing alligator cracks, potholes, flushing, and ravelling. Images portraying various distress types are acquired through crowd-sourcing methods utilizing Mobile Cameras. These images play a pivotal role in validating the object detection model. Figure 2 shows the diverse distress types captured via mobile cameras within the study area.

3. Data Used

The study employs the UAV Asphalt Pavement Distress Dataset (UAPD) by (Zhu et al., 2022) to construct an object detection model. This dataset comprises 3151 images depicting various pavement distress types, such as transverse, longitudinal, oblique cracks, alligator cracks, potholes, and repairs. The acquisition involves using an M600 Pro UAV and a Sony Alpha 7R III digital camera, boasting a 3mm focal length, 7952x5304 pixels resolution, and a frontal overlap of 75%.

4. Methodology

Several sequential steps are undertaken to establish an automated method for the Pavement Condition Index (PCI) estimation utilizing deep learning techniques. Initially, deep learning algorithms are employed to detect and categorize diverse distress types present along road sections. Subsequently, automated equation-based and semi-automated ASTM graph-based techniques are utilized for PCI estimation. A manual method based on the SP-024 manual by the Ministry of Transportation (MTO) is also used. Finally, the PCI estimation outcomes are integrated with Geographic Information Systems (GIS) for visualization. The comprehensive methodology employed in this study is visually illustrated in Figure 4.

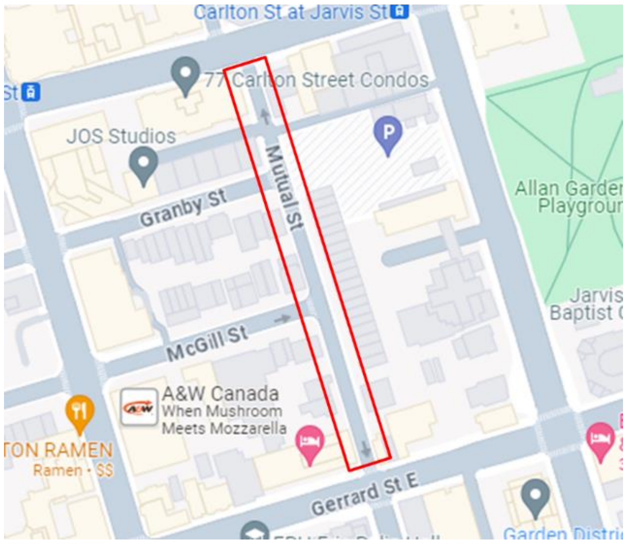


Figure 1. Study area.

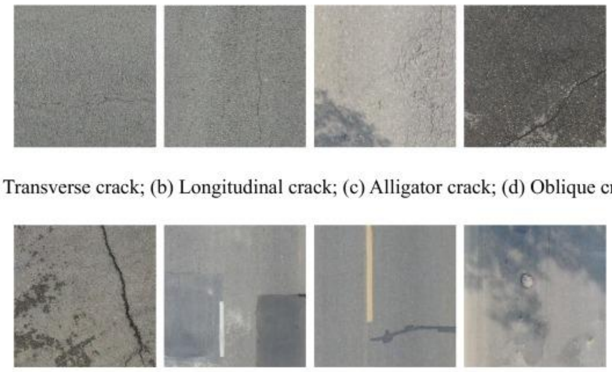
(Source: Google Maps (n.d))

a. Raveling
b. Flushing
c. Rutting
d. Alligator Crack

Figure 2. Field observations.

4.1 Object Detection Model

The primary aim of this stage involves developing an object detection model using deep learning methodologies to effectively identify, categorize, and pinpoint pavement distress. For this purpose, the model is trained to leverage the UAPD dataset detailed in Section 3. Convolutional Neural Network (CNN) algorithm -You Only Look Once version 5 (YOLOv5), enables the distress detection process from the images. YOLOv5 incorporates a backbone that operates on either GPU or CPU for pre-training alongside a head responsible for predicting classes and bounding boxes. This head features a one-stage dense prediction approach and integrates a feature fusion network layer (Neck) between the backbone and head to compile feature maps.



(a) Transverse crack; (b) Longitudinal crack; (c) Alligator crack; (d) Oblique crack

(e) Oblique crack; (f) Repair; (g) Repair; (h) Pothole

Figure 3. Distress types in the UAPD dataset.
(Source: Zhu et al., 2022)

Figure 5 illustrates the model architecture for the YOLOv5 model. The input images from the UAPD dataset undergo initial processing via an input layer and are subsequently forwarded to the backbone for feature extraction. The backbone comprises multiple CBS (Conv + BatchNorm+ SiLU) modules, C3 modules, and a Spatial Pyramid Pooling-Fast (SPPF) module, augmenting the backbone's feature extraction capabilities. The resulting feature maps of various sizes are fused by the neck employing Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) operations, thereby generating comprehensive feature maps. These maps enable the detection of small (P3), medium (P4), and large (P5) objects within the images. The subsequent stage involves directing these feature maps to the prediction head. Here, confidence calculations and bounding box regression occur based on preset prior anchor information, culminating in creating a multidimensional array (BBoxes). This array encompasses object class, class confidence, box coordinates, and width and height data. The final information regarding detecting distinct cracks is obtained through a non-maximum suppression (NMS) process. The model is trained to detect six types of cracks: transverse, longitudinal, oblique, alligator, potholes, and repairs.

4.2 PCI Estimation

The Pavement Condition Index (PCI) indicates the condition of a chosen road segment. This study exclusively focuses on PCI derived for surface distress conditions in flexible pavement. The assessment encompasses semi-automated and automatic PCI estimation methods that utilize road pavement's distress data obtained through the object detection model. The following sections describe each process in detail.

4.2.1 Semi-automated method

In the Semi-Automated method, distress manifestation analysis relies on the object detection model developed in Section 4.1. utilizing Google Street View images. This method aligns with procedures outlined in the ASTM standard. Calculating the PCI value necessitates three key parameters: distress type, severity, and density. The distress type parameter is derived from the object detection model introduced in Section 4.1. The density value is the ratio of the area of the bounding box of the detected crack to the total area of the image. The severity value estimation requires manual interpretation, relying on visual crack examination from the crack image. The PCI value is estimated based on crack type, density, and severity based on ASTM standards. Employing the deduct value graph for each distress based on the ASTM method, the algorithm yields the deduct value once the severity is provided. Upon assessing the seriousness of each crack in the considered segment, the model offers a Corrected Deduct Value (CDV) and the Total Deduct Value (TDV) of the road segment. The PCI value is subsequently calculated based on the CDV against TDV, determined by the CDV versus TDV graph of the ASTM method.

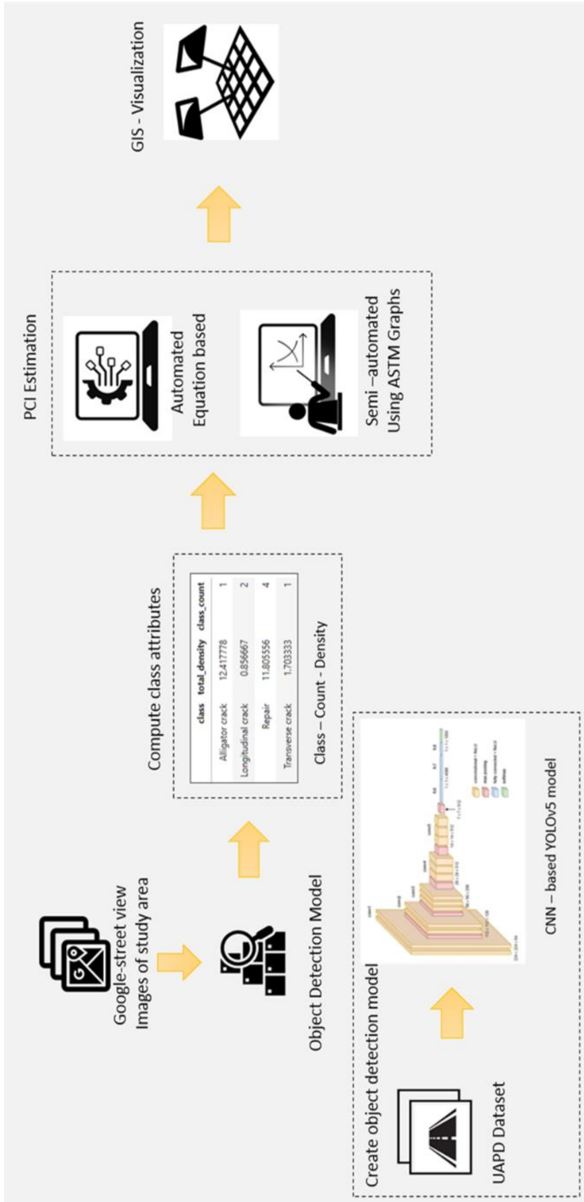


Figure 4. General Methodology.

4.2.2 Automated equation-based method.

The automated method is based on the Adjusted Urban Pavement Condition Equation for flexible pavements established by Osorio et al. (2014). In Equation 1, several variables are outlined. FC denotes the percentage of Fatigue cracking, TRC represents the combined value of transversal and reflection cracking, DP signifies the deteriorated patch, R stands for rutting (mm) derived as the average rutting across segments in the sample unit, and P indicates the percentage of Potholes. All variables used in the equation are acquired through the object detection model. Subsequently, the algorithm autonomously computes the PCI value for each section along the road segment.

$$UPCI = 10\text{-}0.038\ FC\text{-}0.040\ TRC\text{-}0.046DP\text{-}0.059R\text{-}0.237P \quad (1)$$

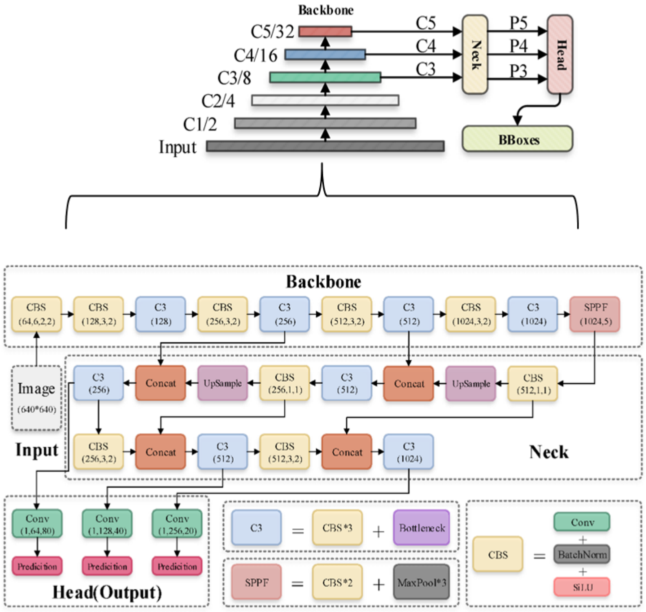


Figure 5. YOLOv5 model architecture.
(Source: Liu et al., 2022)

4.2.3 Manual Method

A manual method is also performed based on the guidelines outlined in the SP-024 manual by the Ministry of Transportation (MTO). This evaluation operates on a scale ranging from 0 to 100. The traditional manual process for Pavement Condition Index (PCI) estimation, following SPC-024 (Manual-Condition-Rating-Flexible-Pavements, n.d.), involves several specific steps. Firstly, a visual inspection is conducted by driving through the pavement to evaluate its overall surface condition. Subsequently, the Ride Condition Rating (RCR) is obtained to assess the pavement's functional condition. Once the RCR is determined, a slow drive over the pavement is undertaken to examine the type and severity of distress present manually. This information is then recorded in the Pavement Condition Rating Form, encompassing the RCR and all observed distress manifestations. Finally, the Pavement Condition Rating (PCR) is assigned according to the guidelines outlined in Table B-1 of the SP-024 manual for estimating pavement condition rating for Flexible Pavements.

4.3 GIS Integration

Geotagged image coordinates sourced from crowd contributions are extracted and systematically stored within a spatial geodatabase. The road section's shapefile is segmented based on geocoding principles within a GIS platform. The PCI derived from the methodology above, specific to each road segment captured in these images, is linked as an attribute within the geodatabase corresponding to these spatial coordinates. Subsequently, the PCI values are visually represented for each of these segments. Finally, a GIS dashboard is created to display the PCI estimation results.

5. Results and Discussions

This section delves into the outcomes derived from the preceding case study. Constructed using the UAPD dataset, the object detection model is tested using Google Street View images. Subsequent sections will intricately detail the results.

5.1 Pavement Distress Detection Modelling

The pavement distress detection's object detection model is developed on the Google Colab Cloud Server, employing a Python-based algorithm. The UAPD dataset is partitioned into 70% for training, 20% for testing, and 10% for validation. The training graphs of the model are depicted in Figure 6. Figure 7 illustrates a model test output demonstrating the detection of a transverse crack from an image.

Evaluating the overall model performance relies on the confidence curve. Analysis of the crack classification model highlights the importance of balancing precision and recall for optimal performance. The F-score reaches an optimal point, indicating a trade-off between minimizing false positives and negatives. This suggests the need for model refinement and careful calibration of the confidence threshold. The highest F1 score pertains to Repairs, implying that the model has a clearer distinction for identifying 'Repair' cracks compared to other classifications. The evaluation of the crack classification model reveals a trade-off between the model's ability to identify true positives (precision) and its capacity to capture all relevant cracks (recall). This suggests that the model could benefit from further enhancements to improve its classification accuracy. The analysis also highlights the importance of balancing recall and the model's confidence threshold. This balance is crucial for optimizing the model's performance in classifying pavement distress effectively.

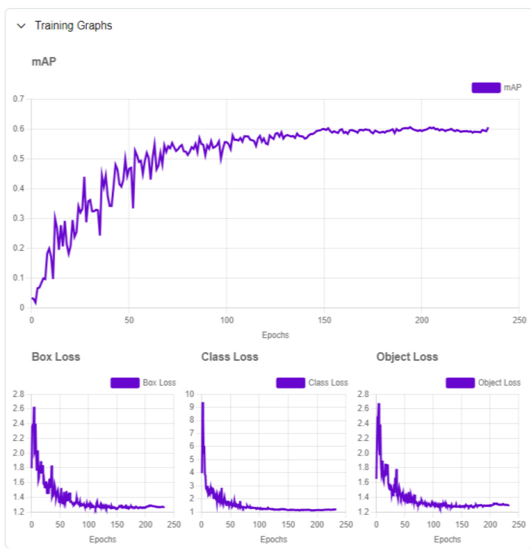
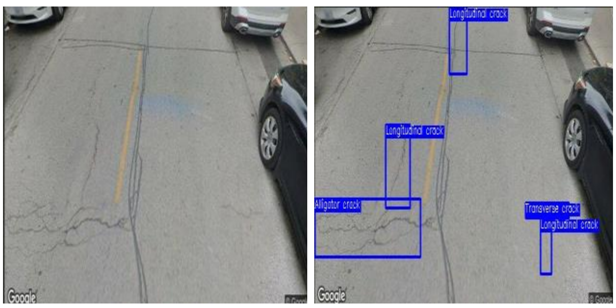


Figure 6. Training graphs.

Figure 7. The output of the object detection model.

5.2 Crack identification

The model created is employed for distress analysis within the study area. Utilizing Google Street View images specific to the study region, the model accurately identifies various types of cracks within the region and computes the Pavement Condition Index (PCI) for individual road segments. Figure 8 shows the model's proficiency in detecting and classifying different crack types within the imagery, demonstrating its capability. Moreover, Figure 8. c details the total density and count of classes identified within the provided image.
The model could be used with crowdsourced images like dashcam videos and phone photographs. This aspect requires further investigation.



a. Input image b. Crack identification

class	total_density	class_count
Alligator crack	12.417778	1
Longitudinal crack	0.856667	2
Repair	11.805556	4
Transverse crack	1.703333	1

c. Class-Count-Density

Figure 8. Crack detection and classification by the model.

5.3 PCI Estimation

The PCI estimation is conducted independently using manual, automatic, and semi-automatic methods, aligning with the methodology outlined in Section 4. The manual evaluation involves completing the flexible pavement condition assessment form by inspecting the road segment and determining the pavement condition rating. According to the manual assessment, the designated area exhibits a PCI value between 20 and 30, indicating poor pavement condition. The evaluation highlights moderate alligator cracking alongside extensive, severe cracking and dishing.

Table 1 outlines the PCI values attributed to various road segments derived from each image based on the semi-automated ASTM-based method and the automated equation-based method. Additionally, Figure 9 depicts the correlation between these two methodologies, revealing a notably strong correlation. This suggests that the UPCI method could replace both manual and semi-automated approaches, offering substantial time-saving benefits.

Additionally, Figure 10 presents the GIS-based visual representations generated utilizing the standard PCI rating scale. ArcGIS Pro serves as the tool for executing the GIS visualization process. The integration of GIS visualization plays a pivotal role in identifying specific road sections necessitating urgent maintenance and repair interventions. Furthermore, the results of the PCI index are displayed in a GIS Dashboard, as shown in Figure 11.

Image Name	PCI_ASTM (Semi-Automated)	UPCI (Automated)
Image_0	96	95.9
Image_1	92	97.8
Image_2	82	75.1
Image_3	78	86.7
Image_4	95	99
Image_5	50	62
Image_6	84	92.7
Image_7	46	73.14
Image_8	60	51.63
Image_9	75	72.1

Table 1. PCI Values for Semi-automated and automated methods.

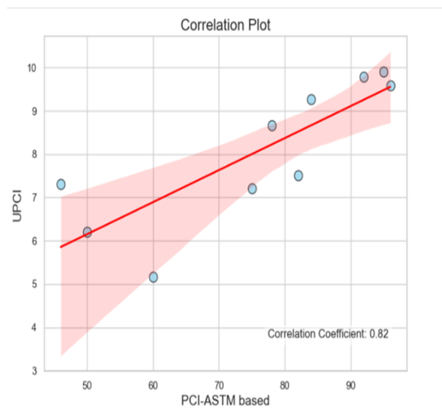
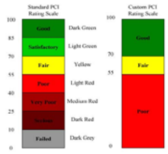


Figure 9. Correlation plot between UPCI and PCI-ASTM method.

a. PCI_ASTM



b. ASTM rating scale

c. UPCI

Figure 10. Results of PCI estimation.

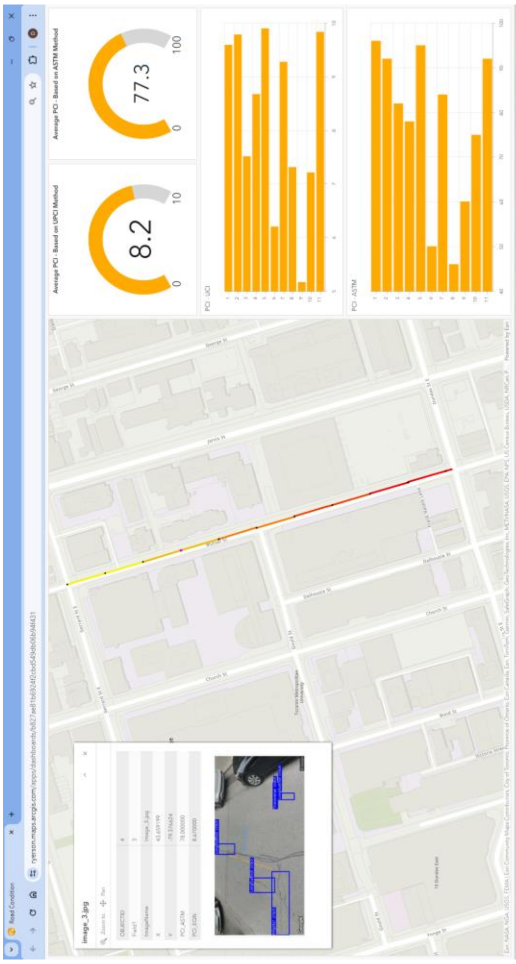


Figure 11. GIS Dashboard.

6. Discussions and Conclusion

The degradation of asphalt concrete pavement significantly affects roadway functionality. Pavement distress amplifies notably, especially under increased traffic loads and over the pavement's service life. Consequently, transportation authorities are facing the ongoing necessity of diligently assessing pavement conditions and formulating appropriate maintenance strategies. A critical metric employed for this assessment is the Pavement Condition Index (PCI), graded on a scale from 0 to 100, where 0 signifies the poorest condition and 100 is the optimal.

Traditionally, PCI determination relies on field assessments entailing manual observation and interpretation. However, this study aims to reform this process by automating it. It involves developing a comprehensive system incorporating a deep learning-based object detection algorithm for pavement distress identification, equation-based PCI estimation, and Geographic Information System (GIS) visualization. As part of this initiative, the study executes manual, semi-automatic, and automated PCI detection specifically for Mutual Street.

The manual method effectively serves targeted data collection without relying on sophisticated technologies. It offers immediate local insights through direct observation. However, its drawback lies in being time-consuming and labour-intensive, thus incurring higher costs. Moreover, subjectivity in interpreting distress types and severity introduces potential inconsistencies and errors. Data collected through this method tends to be less comprehensive and challenging to analyse on a larger scale.

Contrarily, AI-based technology demonstrates efficiency in terms of time and cost by swiftly assessing extensive areas. It presents greater consistency by mitigating human biases and, through appropriate training, holds promise in forecasting future road conditions. However, the initial setup cost involves investing in technology, as classification accuracy hinges on effective model training and substantial initial data collection. Moreover, the model's performance heavily relies on data quality and may overlook subtle details perceivable by a human inspector. Continuous updates and maintenance also form crucial requisites for sustained model accuracy and functionality.

The model was trained on UAV images, yet it remains effective on Google Streetview images for two main reasons. First, the robustness of the CNN algorithm enables it to learn edges, textures, and patterns across diverse views and perspectives, effectively accommodating the differences between UAV and ground images. Second, the appearance of crack patterns is similar between the two types of images; both are represented in 3-channel RGB format and look nearly identical despite their differing viewpoints.

The results from both the equation-based and semi-supervised AI methods display a notable correlation, revealing a fair to poor road condition along the specified stretch. However, the model devised in this study encounters reduced classification accuracy due to diverse distress types. Improving the model's performance entails expanding the array of classes and honing its accuracy through training enriched with crowd-sourced images. Another limitation of the model lies in utilizing bounding boxes for distress density calculation. Introducing image segmentation coupled with distress classification proves advantageous in delineating distress areas and precisely identifying their density. This integration facilitates a more accurate understanding of distress distribution and density across the pavement surface.

Future work encompasses the integration of a crowd-sourcing platform to collect additional road condition data for real-time updates. While the current study leveraged GIS solely for visualization, future endeavours aim to delve deeper into GIS potentialities. This involves exploring spatial dependencies, such as the impact of traffic flow, business activities, and other pertinent parameters, to uncover further insights into pavement conditions.

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