ICBC - MDS Capstone Project Proposal Report

Image Recognition of Vehicle Odometer Readings

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Executive Summary

The Insurance Corporation of BC (ICBC) seeks a solution to streamline the process of verifying odometer readings for their "low-kilometer discount" program. The solution should reduce the manual effort while ensuring high accuracy and reliability. Our proposed data product aims to address this challenge by developing a functional computer vision pipeline. Our pipeline will provide mileage predictions with confidence levels from raw odometer readings. The confidence levels support visualizations of the tradeoff between model accuracy and the volume of photos that are being processed by the model, supporting further model tuning. Recommendations are provided to improve the workflow to reduce the degree of manual verification and to enhance the workflow robustness.

Introduction

The Insurance Corporation of British Columbia (ICBC) is a provincial Crown corporation established in 1973 to provide auto insurance to drivers in British Columbia. ICBC offers premium discounts to drivers who travel below a specific annual mileage threshold. To verify the mileage, drivers are required to upload a photo of their vehicle's odometer, and the photo is manually reviewed by ICBC employees.

The manual verification process has become impractical in terms of time and resources as the volume of submitted images grows. Relying solely on manual review for obtaining odometer readings introduces the possibility of inaccuracies and unreliability. Such errors can lead to severe consequences, including allegations of fraud, customer dissatisfaction, and damage to the company's reputation. ICBC is seeking a technological solution to tackle these challenges. Our objective is to address this issue by leveraging computer vision and machine learning techniques. We aim to provide a solution that offers precise and reliable annotation of odometer readings, specifically tailored to support ICBC's low distance insurance program and alleviate the manual workload for employees.

Objectives

This project will explore the viability of automating the odometer verification process and present a workflow that addresses the following primary objectives:

- Develop a solution that emulates the manual odometer verification process, with the following elements:
  - accurately identifying the region of the odometer in an image
  - extracting the displayed mileage
  - providing confidence metrics for each digit and the overall reading
- Provide an interactive demonstration of the system, showcasing its capabilities and highlighting the potential benefits it offers.
- Identify limitations and challenges of bringing the system to production. Factors such as lighting conditions, image quality, and variations in odometer designs can impact the system's accuracy and recognizing these limitations is vital to establish realistic expectations and define the boundaries of the system's performance. The impact of the system extends to key stakeholders, including ICBC and insurance customers. Please refer to Appendix 1 for a detailed overview of the stakeholders' interests.

The primary goal is to demonstrate the effectiveness and reliability of the system, with a focus on achieving a high accuracy rate. In a production environment, where maintaining a positive reputation is vital, ensuring a minimum accuracy level of 90% is crucial. This establishes a strong foundation for future improvements and advancements, and proves the system's ability to deliver reliable results in real-world scenarios.

Dataset

Figure 1 shows the sources of our data for training and testing our models. ICBC initially provided a dataset comprising 19,038 images of odometers, which included metadata annotations for the Make, Model, and Year of the vehicles. This dataset lacked annotations regarding the location of the odometer and its digits, which is essential for training object detection models. To address this, we annotated a subset of 7,606 images by adding bounding boxes around the odometers. In addition, we used publicly accessible online datasets from a platform called Roboflow that came with already annotated images of different digits. Finally, our test data was a second batch of 6677 images from ICBC. Each image was accompanied by a verified odometer reading, enabling us to compare this value with the predictions made by our models.

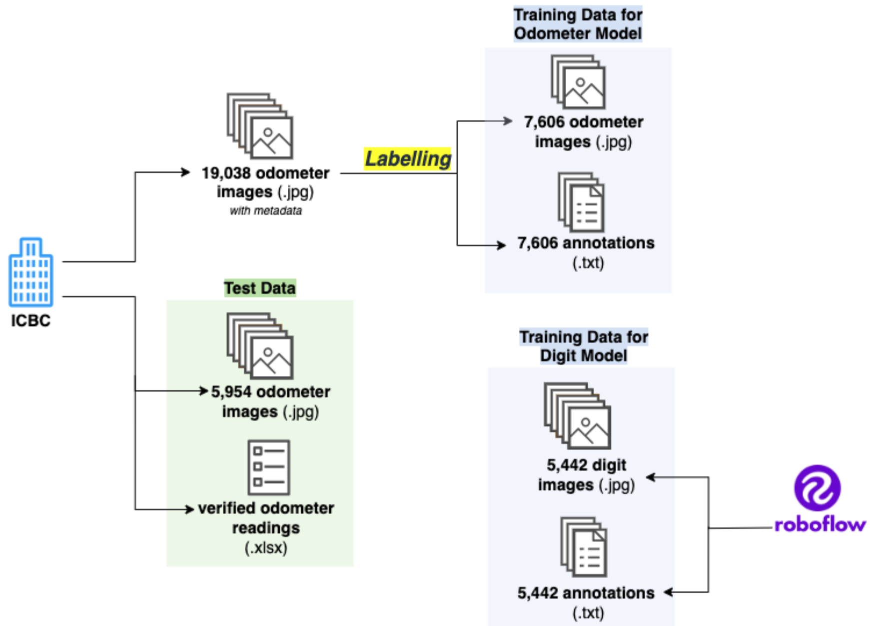


Figure 1: Sources and Preparation of Train and Test Data: During the labeling process, text files are created for each image, specifying the coordinates of the odometer and digits within the images. These files, along with the images, are then used to train the object detection models. For testing, ICBC provided a spreadsheet with verified odometer readings for each test image and these readings were then compared to the predictions of our models.

Data Science Methods

Pipeline

We initially experimented with programs such as EasyOCR and Tesseract. We discovered the limitations of the initial optical character recognition (OCR) approach for our project due to the substantial visual complexity in dashboards and the abundance of irrelevant numerical data.

We chose an alternative approach, depicted in Figure 1, where we employ two object detection models at different stages, each serving a specific purpose: (1) for identifying the location of the odometer and (2) for identifying the digits in the odometer. The process begins by resizing an input image to a maximum width or height of 1280 pixels. The resized image is then passed through the first model, the odometer detection model, and a prediction is made for the location of the odometer. The image will be cropped according to this prediction and resized to a maximum width or height of 320 pixels and inputted into the second model, the digit detection model. At the end of our pipeline, a JSON file is generated as output. This file will includes the odometer reading along with confidence levels for the odometer identifiation and each identified digit. Additionally, the reading is subject to further filtering. For instance, the system checks if the prediction contains an excessive number of values. If it does, only the first six values are presented.

Modeling

We used YOLOv8 (You Only Look Once)[1], an object detection model developed by Ultralytics for both the odometer detection model and the digit detection model. YOLOv8 performed better than an alternative

[1]Redmon, J., Divvala, S., Girshick, R. and Farhadi, A. (2016) You Only Look Once: Unified, Real-Time Object Detection. IEEE Conference on Computer Vision and Pattern Recognition, Las Vegas, 779-788. https://doi.org/10.1109/CVPR.2016.91

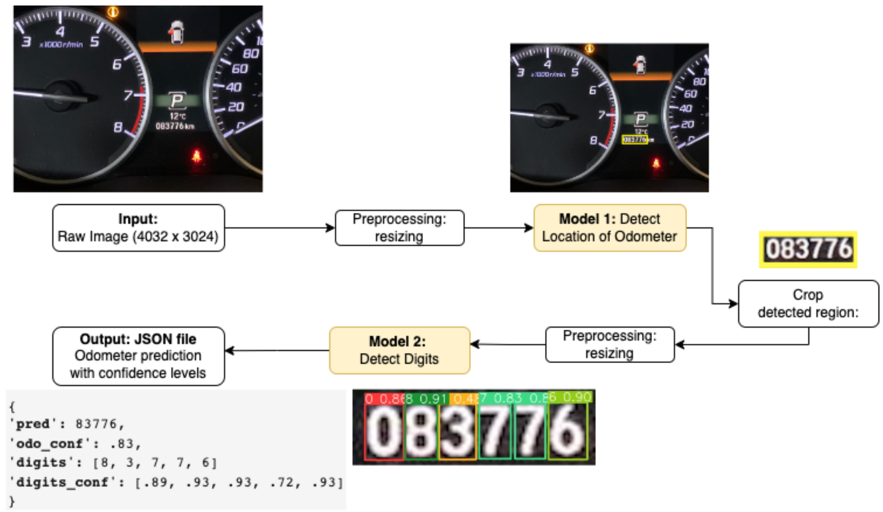


Figure 2: Odometer Reading Pipeline: The process of going from an input image to an odometer prediction with confidence levels.

model we experimented with called FasterRCNN[2]. It was easier to implement, offered quicker training and prediction speeds, and required a smaller amount of data to achieve satisfactory results, which was a significant consideration for us as we annotated our own training data.

When training our Yolov8 models, we resized and added padding to the images to achieve a square shape. Following this step, the pixel values were normalized, and the images were converted into tensors for further processing. For the odometer identification model, we selected an image size of 1068 pixels by 1068 pixels, which served as a suitable midpoint for accommodating the varying image sizes in our dataset. As for the digit model, we opted for an image size of 320 pixels by 320 pixels.

Figure 2 displays the output at the end of our pipeline: a JSON file containing the predicted odometer reading and confidence levels for both odometer identification and individual digit predictions. Notably, the predictions of the odometer include all odometer predictions and all digit predictions, even those predicted with a very low confidence level. Figure 3 demonstrates the relationship between the minimum confidence level of digit predictions and the accuracy of the overall prediction. By applying a threshold to this confidence level, uncertain predictions can be filtered out, leading to improved accuracy. In the Results section, we will explore how ICBC can utilize this filtering mechanism for improved results.

[2]Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. In *Advances in Neural Information Processing Systems (NIPS)*.

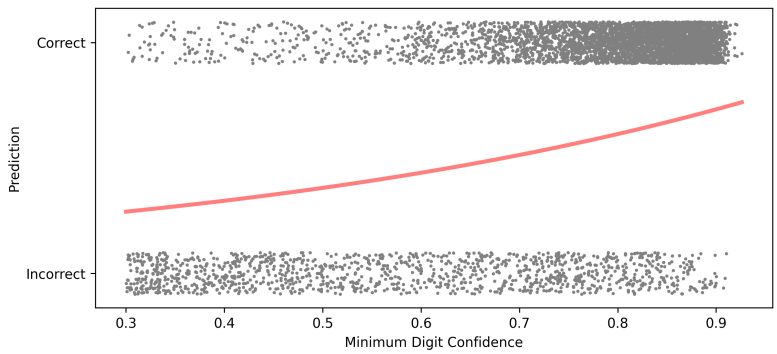


Figure 3: Minimum Confidence Level of Digits vs. Prediction Accuracy: The gray data points represent the minimum confidence level of the digits in the prediction and indicate whether the prediction was correct or not. The red curve illustrates the trend of higher prediction accuracy with higher minimum confidence, meaning if the model is unsure about one of it's digit predictions, the prediction is likely to be wrong.

Results

As our two models are detecting two different things, we have to set different probability thresholds for defining detection.

For the odometer detection, we started out with our entire test set of 6677 images. We set a threshold confidence threshold of 0.75, so that if the model predicts an odometer, it is predicting it with a high confidence. Out of all the images, we detected an odometer in 5115 images, at a detection rate of 77%. The remaining 23% does contain images where there is an odometer but the model was not able to detect it, possibly because the image is not clear enough or the image is of a vehicle of a newer model that is underrepresented in our training data. Of the 77% of odometers detected, we have a success rate of almost 99.9%, meaning if there is an odometer detected with confidence by our model, we are right about it almost 99.9% of the time. There are 6 images where an odometer was detected in a non-odometer image. Overall, this model achieved impressive results despite the variability in photographed dashboards.

For digit detection, we set a higher threshold for the mileage detection at 0.85 because detection of the digits turned out to be a much more complicated process. We needed a higher threshold to be able to distinguish between similar looking digits like 1s and 7s, and 3s and 8s, such as in Figure 2. Out of the 5115 identified odometer regions from the first model, digits were detected in 3529 cropped images at a confidence level of 0.85 or higher (69% detection rate). This second model in our pipeline did not perform as well in detection, potentially due to the usage of online public digit datasets rather than our own dashboard image data. Of the 3529 of cropped images that there was a detection, 3365 were read correctly, resulting in a success rate of 95%. This means that if our digit detection model was confident in it's predictions, it was correct 95% of the time. The 5% of images where the model predicting incorrectly with confidence can potentially be reduced by setting rules on the predictions, for example, restricting the odometer prediction to be higher than the policyholder's mileage from the previous year.

Figure 5 presents the distribution of the test set as it progresses through stages of our pipeline. Initially, images undergo a filtering process using the confidence thresholds. If the odometer prediction confidence is low or there is no odometer predicted by the first model, the images are subjected to manual review. In the next stage, digit predictions are made, and if the confidence levels falls below a specific threshold, the images are passed for manual review. Images that successfully pass both stages are returned with predictions, enabling us to visualize the count of correct and incorrect predictions.

Out of our test dataset, a total of 3148 images were rejected based on confidence thresholds of 0.75 for the odometer detection and 0.85 for the digit detection, and these images were rejected for manual review. The number of images that would be require manual verification reduced from 6677 to 3148 images, a decrease of 53% while maintaining an accuracy of 95%.

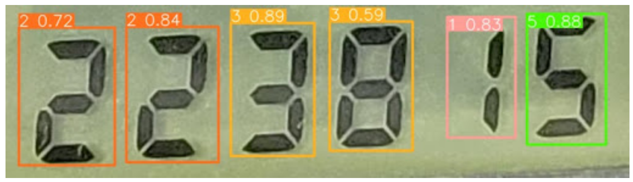


Figure 4: Misidentification of Digits: The digit model wrongly identified a 3 as an 8 in this prediction, and the confidence level for this digit is noticeably lower compared to the others at 0.59. At a confidence threshold higher than the average confidence level of all the digits, this photo would be rejected and sent to manual review.

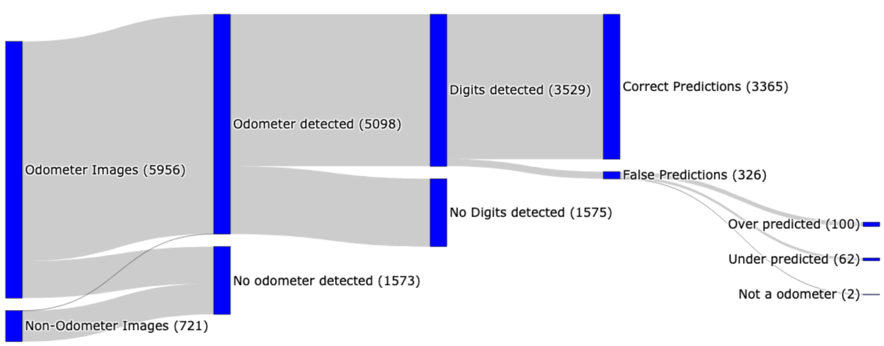


Figure 5: The flow of test images through our pipeline

Lowering the thresholds can potentially improve accuracy by lowering the number of false predictions. It would result in more images being rejected along the prediction pipeline and increase the number of images needing manual review.

ICBC places a strong emphasis on high confidence and prediction accuracy, considering the potential impact of incorrect predictions on costs and reputation. However, to make the process more efficient and reduce the need for manual verification, there are situations where a slight decrease in accuracy might be tolerated in order to include more images in the automated process.

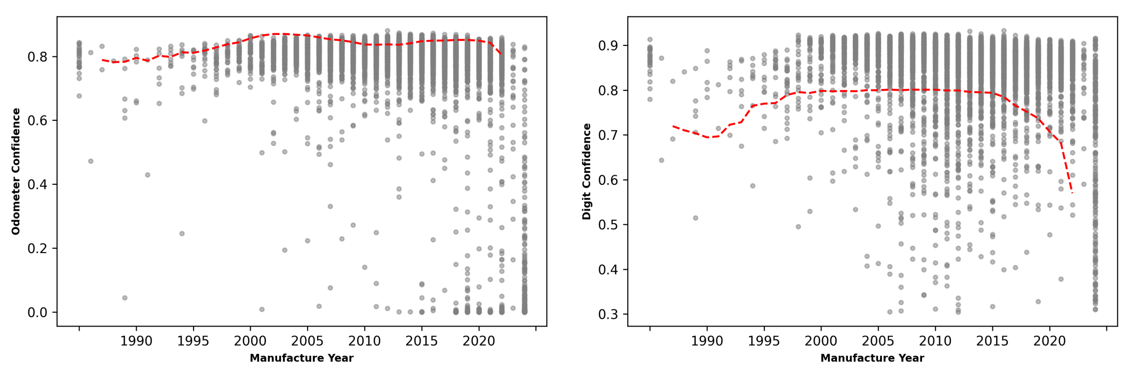
Thus, finding the optimal threshold involves balancing accuracy, operational efficiency, customer satisfaction, and the need for manual verification, aligning with ICBC's operational goals.

Ethical concerns

It is crucial to recognize and mitigate potential ethical considerations related to image quality, variations in cameras, and vehicle characteristics, as these factors could be linked to a person's socioeconomic status. To determine the make, model, and manufacturing year of vehicles, we used the VIN (Vehicle Identification Number) associated with the insurance policy and the submitted image. Our analysis of the test set demonstrated no significant correlation between vehicle attributes and the confidence levels of the models, as illustrated in Figure 6.

We did notice a slight decline in the confidence levels of odometer predictions in recent years (Figure 7a), which can be attributed to the introduction of new methods of displaying odometers in newer vehicles, including smartphone applications and integrated LCD screens. Our model was not trained specifically on these advanced methods, which may contribute to the lower confidence levels observed.

The fluctuation in the average confidence levels of both models during the earlier years, specifically up to 1995, can be attributed to the limited availability of images for older types of odometers.



(a) Odometer Confidence by Manufacture Year

(b) Digit Confidence by Manufacture Year

Figure 6: Models' Confidence by Manufacturing Year: Each point on the plot represents a prediction, showing the manufacturing year of the photographed vehicle and the confidence levels of the odometer detection model and the digit detection model. The red line depicts the average confidence level for each year.

In our analysis, no significant relationships were found between image attributes and model confidence. However, it remains crucial to further investigate this aspect to ensure fairness for all users and mitigate potential issues like slower verification times, unfair denial of benefits, or inaccurately assigned lower rates that could arise from varying levels of access to high-quality cameras.

Continuous evaluation of the model with a focus on ethical considerations should be an ongoing practice to ensure fairness and accuracy in its broader implementation..

Data product

Our data product is a web app that provides a user-friendly interface for the partner to interact with and analyze the results of our model. The web app consists of two tabs as shown in Figure 7.

In Tab 1 (Figure 7a), the user can upload an image to see how our models perform on that specific image. The results are displayed as the original image with the predicted location of the odometer and the predicted digits in the cropped image. A table will display the confidence levels, with any confidence below a specified value highlighted in red.

Tab 2 (Figure 7b) presents the Sankey Diagram from Figure 5 where the user can adjust the confidence thresholds for both models using a slider. This feature shows the impact on the number of rejected images requiring manual review and the number of images processed through the pipeline for predictions. It provides valuable insights into the trade-off between accuracy and the quantity of predicted objects.

Pros of using this product include its user-friendly nature, making it easy for executives and non-technical stakeholders to understand and interpret the model's performance. It also meets the specific requirements of the partner, unlike other alternatives such as notebooks or reports which may lack explainability and interactivity. As a result, the web app provides a balanced solution that is both user-friendly and tailored to the partner's needs.

Enhancements

During the production stage, the pipeline can be integrated into a mobile or web app, providing customers with a convenient and efficient method to verify their vehicle odometers. The app can incorporate non-ML solutions, such as rejecting images that do not meet predefined criteria before processing. Additionally, the app can offer users comprehensive instructions and guidance on capturing suitable odometer photos, using visual prompts, step-by-step instructions, or real-time feedback. This helps users position their cameras accurately and avoid common issues like reflections or blurriness. By excluding low-quality or irrelevant images, the app enhances the likelihood of accurate predictions from our models.

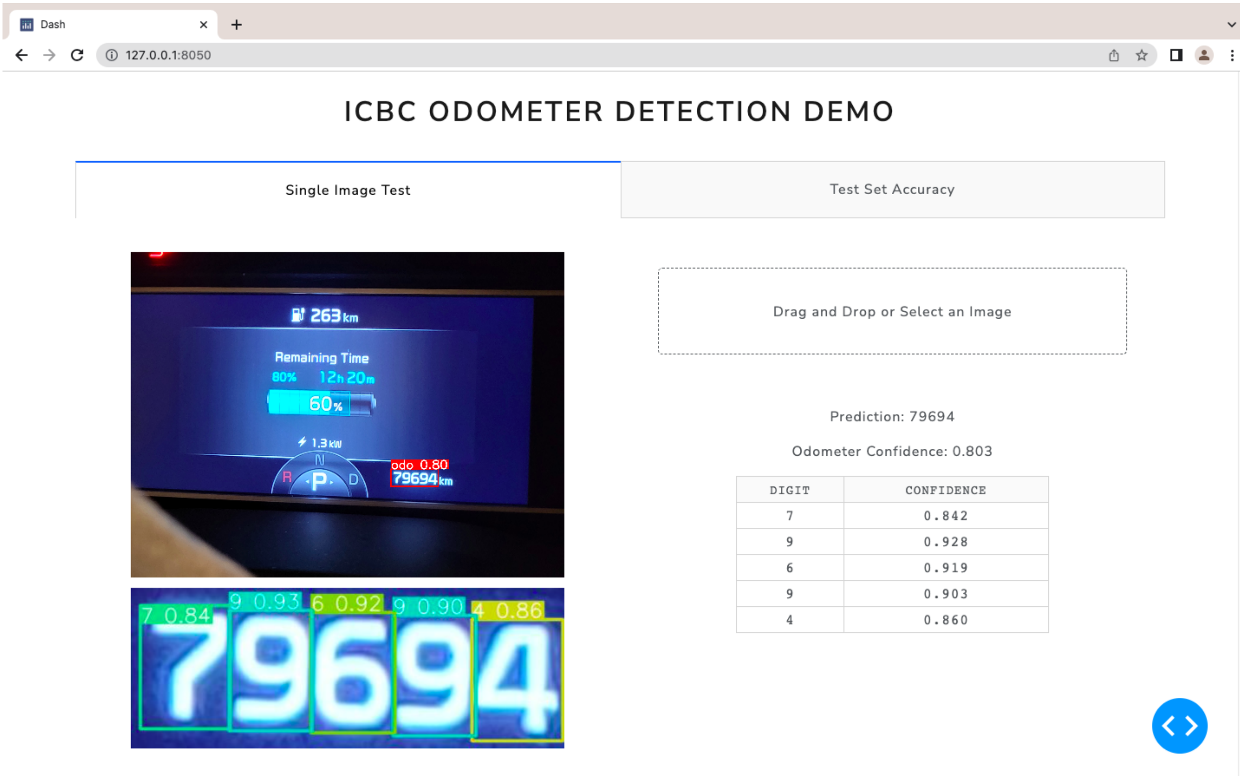
We can also incorporate user verification and correction into the workflow. Allowing users to review and correct the model's annotations on their images would result in more labeled data and valuable insights into models' accuracy. However, due to time and resource limitations, we decided not to implement these enhancements. Our focus was on delivering a functional product considering integrating new processes would require close collaboration with ICBC's internal development teams who have a better understanding of the current infrastructure.

Conclusion

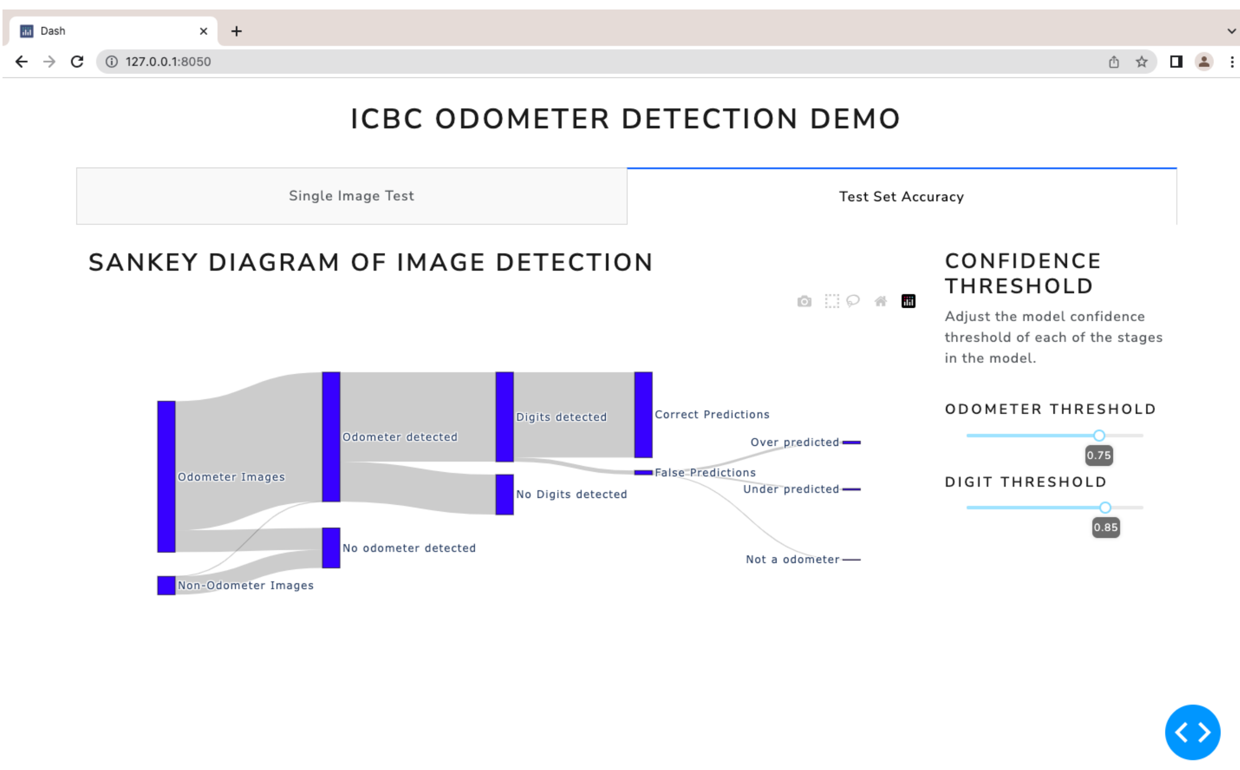
We created a technology solution for ICBC to simplify their "low-kilometer discount program" and reduce manual work. Our product includes a pipeline for predicting odometer readings from images and includes a user-friendly web app for visualizing the results. ICBC can use our product to assess accuracy and reduce manual labor with confidence thresholds, making informed decisions for their discount program.

Although our overall pipeline was a success, our second model for identifying digits didn't perform as well as expected. Nevertheless, there are several opportunities for enhancement. For instance, training the digit identification model using labeled digit images from ICBC can improve its performance. Moreover, developing a user-friendly app tailored to customers can generate more labeled data to be fed back into training the models.

To maintain success and improvement, we suggest continuously evaluating and enhancing the models' performance. This involves monitoring ethical concerns, addressing biases, and gathering feedback from ICBC employees and customers. Regular updates to the models and the app, incorporating new data and technology advancements, will contribute to long-term effectiveness and efficiency.



(a) Tab 1: Single Image Prediction



(b) Tab 2: Interactive Sankey Diagram

Figure 7: The two tabs of the web application.

Appendix A

The following table shows our primary stakeholder groups and detailing the impact of our project outcome.

Stakeholder	Value	Detailed Description
ICBC	Cost Effective	Given a large number of images, the review process should be cheap.
	Reputation	As a public insurer, ICBC is susceptible to public perception and thus carries high reputational risk.
	Speed	Images need to be validated with speed so insurance products can be sold in a timely manner.
	Accuracy	ICBC seeks to minimize the number of images that are incorrectly labeled. Specifically predictions that claim a lower odometer value than actual, thus incorrectly awarding discounts.
Customer (Insuree/Driver)	Speed	Customers want to be able to determine their discount immediately.
	Accuracy	Customers want their discount to be correct and not be surprised by changes later. Customers would be particular concerned with images that claim a higher odometer value than actual, thus incorrectly disqualifying them from discounts.
	Scrutiny	Customers do not want their images to be unnecessarily scrutinized.