ICBC - MDS Capstone Project Proposal Report

Image Recognition of Vehicle Odometer Readings

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Executive Summary

The Insurance Corporation of BC offers a discount on insurance premiums to drivers who travel below a certain annual mileage threshold. In order to qualify for the discount, drivers must submit images of their odometers and this mileage is manually verified by a team member at ICBC. This task is time-consuming and demands a high level of precision from the public company, which is accountable to the people of BC. To streamline this process and improve accuracy, we plan to develop a web application that leverages image segmentation and optical character recognition technologies. Our project will address challenges such as variations in image quality, size, and odometer design, resulting in a machine learning workflow that can accurately predict odometer readings, assess precision and accuracy, and provide a means for ICBC to incorporate the workflow into their process for providing low-mileage driver discounts.

Introduction

ICBC is a provincial Crown corporation established in 1973 to provide compulsory auto insurance to all drivers in British Columbia. It presently offers discounts to its customers who drive fewer kilometres than a specified amount in a year, referred to as “low-kilometre” discounts. To verify the low mileage of their vehicle, customers enter their current mileage and upload a photo of their vehicle’s odometer through a web app. The submitted image is then manually reviewed by a team of workers at ICBC, and the verified odometer information is entered into the customer’s policy record. The issue lies in the significant allocation of time and resources toward manually examining each image. Furthermore, customers experience delays in receiving their discounts while waiting for the manual review process.

The objective of the project is to develop a web application that can take an image as input and use the model to recognize the image as a vehicle, locate the vehicle odometer, extract the odometer number, and provide confidence in the accuracy of the reading. The project’s goal is to ensure that the model achieves a minimum accuracy of 90% to mitigate the potential impact of any inaccuracy on ICBC’s customers in British Columbia and the company’s reputation.

Data Description

Our dataset contains 19038 images of odometer readings captured between 2018 and 2023. Each image contains structured metadata, as presented in Figure 1. Furthermore, we will receive another set of images with corresponding odometer readings, which will serve as our validation set to test the accuracy of our model.

Figure 1: The metadata of each image includes information about the connected policy’s car, such as the make, model, and manufacturing year of the vehicle, which is stored in the form of exif data.

The diversity in the types of odometers displayed in the images is a major challenge that we must address while working with this data, and it poses a significant obstacle to achieving our model accuracy goal of 90%. According to The New York Times, mechanical odometers were replaced with digital odometers in most cars by the early 2000s[1].

Our dataset mainly consists of images of vehicles manufactured after 2000, as depicted in Figure 2, but many cars were still produced before that time. Figure 3 shows the substantial differences between the oldest and newest cars of the subset of data.

[1]Stenquist, P. (2021b, May 20). Odometer Rollbacks: A Hard-to-Spot Nuisance for Car Shoppers. The New York Times.https://www.nytimes.com/2021/05/20/business/odometer-fraud.html?smid=url-share.

Figure 2: Most of the cars in our dataset were manufactured in the past 20 years, with a peak observed around 2005. The red line in the plot represents an approximate time when digital odometers began to replace mechanical ones in most vehicles. However, we also observe a decline in the number of cars manufactured in recent years, which could potentially make it challenging for our model to identify the most advanced odometer displays.

Figure 3: On the left is one of the earliest dashboard designs in our dataset, featuring the mechanical dashboard of a 1965 Dodge Dart model. In contrast, the image on the right displays the fully digital dashboard of a 2021 Audi Etron. The two images demonstrate the remarkable differences in dashboard designs between older and newer cars.

While the majority of our images come from popular car makes that likely use standardized odometers, our dataset also includes many unique vehicles. Therefore, in order to achieve our target accuracy goal, our model must perform well on the less common vehicle types in our dataset, despite their smaller representation.

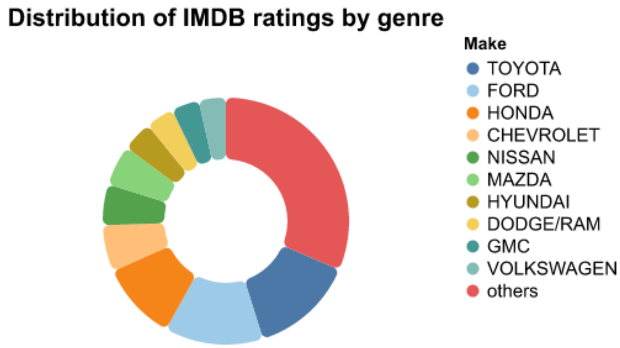
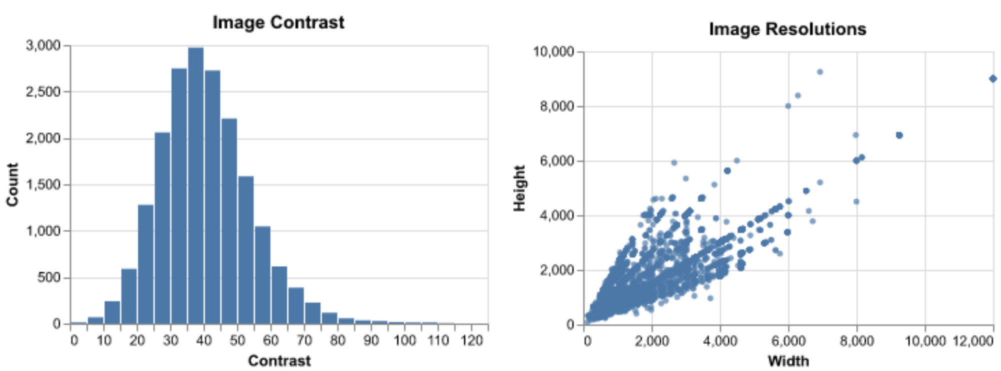


Figure 4: More than 70 percent of the images in our dataset are attributed to the top 10 most prevalent car makes. Among these, Honda, Ford, and Toyota are the most frequent, accounting for 30 percent of the dataset.

Additionally, the quality of the images could also pose a challenge. For instance, figure 5a depicts a significant variation in contrast levels between low and high contrast images. Another challenge with the dataset is the wide range of image sizes with the smallest image at 180 x 320 pixels and the largest image at 12000 x 9000 pixels. This variation can pose a challenge when training a machine learning model, as the input data needs to be consistent in size for the model to learn effectively. Appropriate preprocessing techniques, such as resizing, cropping, or padding, contrast normalization and enhancement, may be employed to mitigate the impact of varying image attributions on the model's performance.



(a) (b)

Figure 5: The images typically have lower contrast levels, which is found by calculating the difference between the lightest and darkest pixel values in the image. The most common range being between 30 to 40. The plot on the right displays the distribution of image size ratios in our dataset. The 4:3, 16:9, and 3:2 ratios are the most commonly used ratios in consumer camera phones, which are the primary source of our data. Both these variations are dependent on various factors, such as lighting conditions, camera angles, camera quality, dashboard design, and more.

The Approach

During scoping, we explored off-the-shelf open-sourced Optical Character Recognition (OCR) tools such as Tesseract and easyOCR. Tesseract, which is optimized for recognizing text from scanners or cameras under good lighting conditions, was largely unable to recognize the text in our odometer images, which had varying font styles, resolutions, and contrasts. EasyOCR performed better, being able to identify an odometer-like value ~30% of the time. While the performance of these tools could be improved via pre-processing, the low accuracy suggests a more involved, specifically trained approach would be more appropriate.

Considering the objective outlined in the introduction, we propose the following pipeline is as described in Figure 6 below. We considered using a classification model as the first step to distinguish dashboard photos from non-odometer images. However, we chose to skip this step and use a segmentation model to detect potential odometer readings. If a potential odometer reading cannot be detected with sufficient accuracy, we can assume it is not an image of a vehicle.

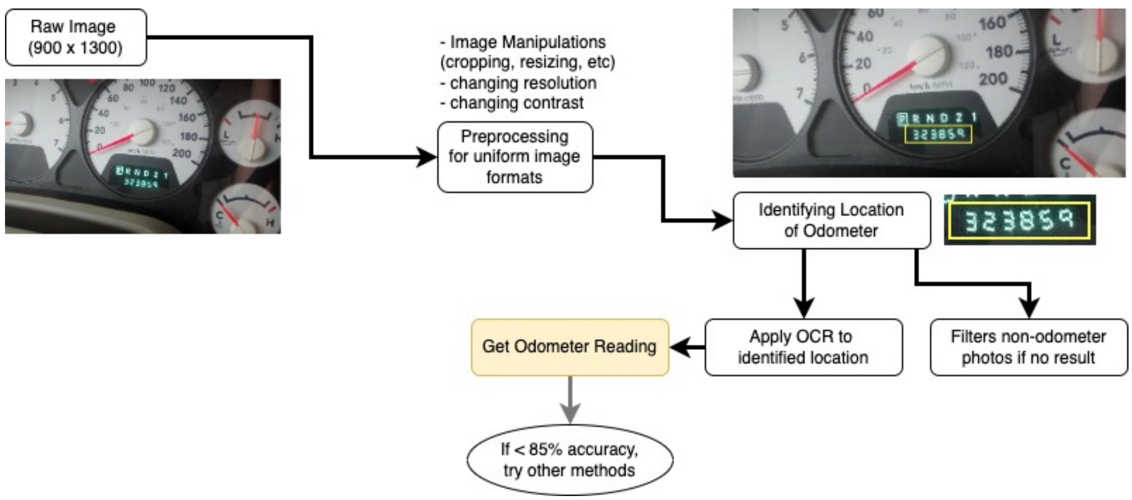


Figure 6: The proposed Pipeline, divided into three separate stages: pre-processing, odometer detection, and value detection.

In the pre-processing stage, image manipulations such as resizing, contrast controls, and filtering will be performed to make input images more uniform. Image segmentation will isolate the odometer region of the image, thereby removing extraneous numerical information such as trip mileage, speed, and temperature. Finally, odometer value detection will use the segmented image to extract the value, while being robust to various types of odometer displays and image quality issues.

The dataset provided by ICBC is expected to be sufficient for these learning tasks. However, for object detection tasks, training typically requires labeled bounding boxes for each object class. This is not provided in the ICBC dataset, only the value of the odometer is provided. While alternative approaches could be employed to simulate the bounding boxes, we have identified "TRODO: A public vehicle odometers dataset for computer vision" as a potential data source with annotations including the bounding boxes of odometer displays. This will allow us to use a industry standard training process and likely improve model performance.

Success Criteria

The primary factor for measuring the success of our model is its ability to produce accurate odometer readings. ICBC has established a minimum accuracy benchmark of 90% to safeguard the company's reputation, as a wrong reading could have adverse consequences. The ratio between over and under-estimation needs to be tracked as each case has different consequences for different stakeholders. In the under-estimation case, the insurer faces a financial loss; in over-estimation cases, the driver does not receive a discount. Furthermore, while a human-in-the-loop system is most likely, the company aims to minimize the need for human intervention, thereby reducing expenses and improving efficiency. Furthermore, a model that can instantly read odometers without requiring manual verification would enable customers to receive applicable discounts, saving them time. With a high level of accuracy, customers eligible for discounts can benefit from cost savings.

Our Timeline

Below are the projected timelines and key milestones for our project:

- **Friday, May 12 - Milestone 1: Scoping Complete**

  By this date, we will have completed scoping the project, which includes fully understanding the problem to be solved, defining the goals and objectives of the project, determining the stakeholders involved, and attempting the initial, fundamental approach to address the problem.

- **Tuesday, May 23 - Milestone 2: Decide on the Best Model**

  By this milestone, we aim to have experimented with various models, determine the optimal approach, and identify the most promising model.

- **Friday, May 26 - Milestone 3: Minimum Deliverable Product**

  We plan to finalize our machine-learning pipeline and ensure the code is no longer confined to notebooks. This milestone marks the minimum product that should be delivered to meet the project's requirements.

- **Thursday, June 1 - Milestone 4: Fine Tuning Complete**

  On this date, we expect to have finished fine-tuning our model and completed thorough testing and evaluation to identify areas for further improvements.

- **Monday, June 12 - Milestone 5: Final Model**

  After milestone four and before this date, we plan to make final adjustments to our model based on the results of our evaluations. We will have finalized the packaging of our model through a web application and created clear and concise, understandable documentation that will be accessible to developers and end-users.

- **Friday, June 16 - Milestone 6: Final Presentations**

  Our final presentations will take place on this date.

- **Wednesday, June 28 - Milestone 7: Final Product**

  By this date, we will have completed our final data product.