1. Introduction

A smart city can be defined as a municipality tasks which utilizes various types of electronic data collection operations in order to gather and provide information to increase operational efficiency, improve the quality of government services as well as the welfare of the citizens while managing resources efficiently. In this sense, inspections performed on cracks that are observed in buildings and/or bridges is an operation that can be addressed via tools of smart cities. In this project, we are first evaluating the current process flow of these operations and then we suggest a solution that will increase the efficiency of building/bridge inspections which will also provide remarkable cost and time savings.

2. Motivation

Infrastructure inspections are one of the crucial elements of preventing possible and even dangerous failures that can decrease the life quality of the citizens. They are also required to be done with specific frequencies by law in Canada. For instance, buildings are required to be inspected every year. According to the Public Transportation and Highway Improvement Act, all provincial and municipal bridges must be inspected every two years [1]. These points indicate that implementing a more efficient method for inspections of both buildings and bridges should be considered as an important application area of smart cities.

A factor that affects the strength and durability of such infrastructures is their age and stage in their lifespan. When buildings or bridges are old and pass around the halfway of their useful life, the probability of observing damages or failures increases. In these cases, inspections should be carried out more frequently to prevent inconveniences such as road closures or building evacuations.

In order to have an idea on the average age of the buildings in Toronto, the map presented in Figure 1 can be examined. This map was developed by the Survey and Mapping Services of the City of Toronto in 2003 and it can be seen that the downtown area consists of mostly yellow and orange colors, indicating that the buildings are mostly constructed at the first decade of the 20th century. Towards the suburban areas, we can see that the age of the buildings decrease, but still red parts are about 60-70 years old, whereas the blue and green parts are 30-40 years old on average [2].

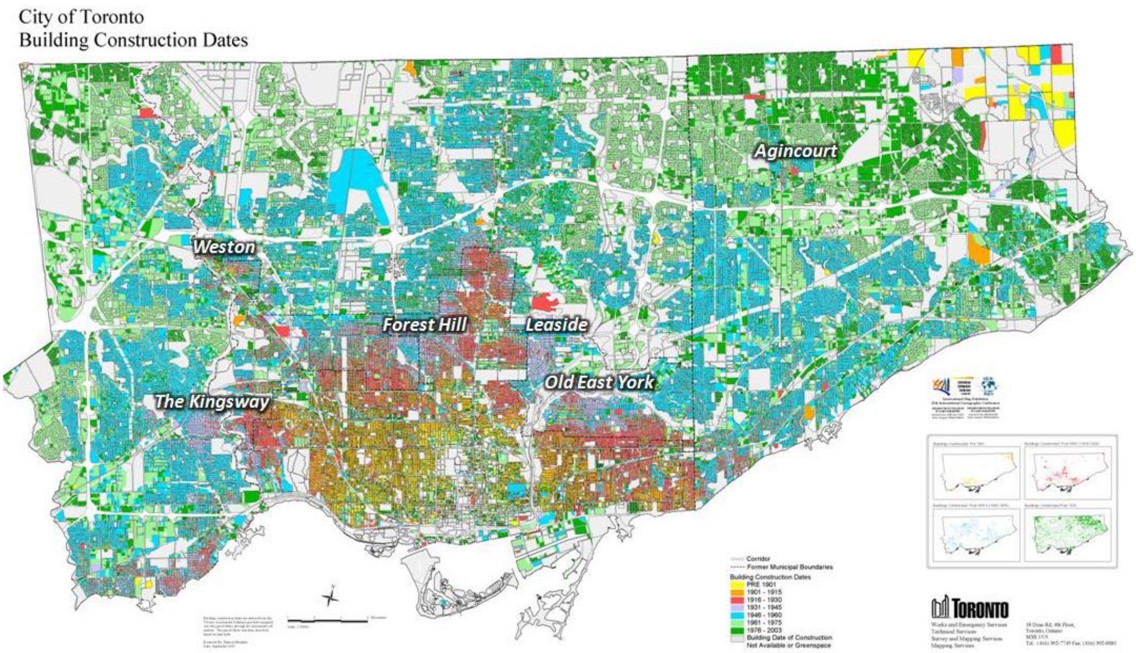


Figure 1: Building Construction Date Map of City of Toronto [2]

When we look at the bridges the situation is not different. There are around 150 bridges in Toronto and 15.000 in the province of Ontario [1]. It is observed that more than 70% of these bridges were built between the years 1950-1980, and that gives an average age of about 40 years. In addition to that, Figure 2 represents the age of bridges in Canada as percentage of their useful life [3]. It can be observed that the bridges in Ontario have already passed the half of their lifespan with 55.7%. At this point, it should also be mentioned that the bridges were expected to last around 60 years in the past; however, with the increasing traffic volume, heavy trucks and excess exposure to salt in winter, their lifespan can get considerably shorter [1].

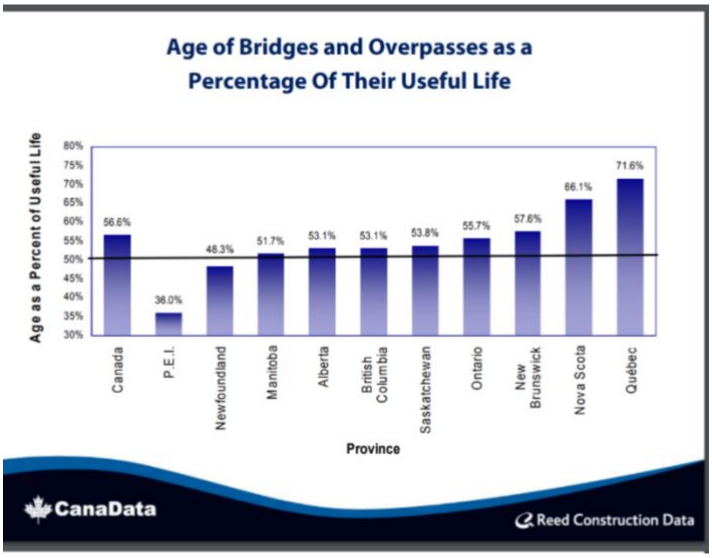


Figure 2: Age of Bridges as a Percentage of Their Useful Life [3]

After determining an average age of 40 years for bridges and even a higher number for buildings, we can claim that the inspections play a more critical role in Toronto compared to other cities that might have lower average infrastructure age. This illustrates one of the main reasons why we would like to address such a problem in the smart city of Toronto.

Another aspect to this problem is the possible expenses. The maintenance and repair operations done on buildings and bridges are significantly high. For instance, 37% of total average infrastructure expenditures are dedicated to non-residential buildings, which is the highest amount compared to other infrastructure categories, and that can be seen in Figure 3 [4]. In addition to that, if maintenance on buildings is not performed on time, repairs equalling five times the maintenance costs are required [5]. Another point that can be made is that the government increased the budget of the next 5 years allocated to maintenance and rehabilitation of the bridges by $450 million in 2009 [1].

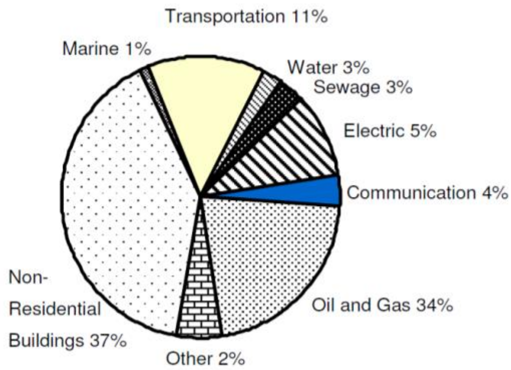


Figure 3: Distribution of Infrastructure Expenses [4]

After observing that maintenance operations are high in cost, we can understand the importance of inspections even better. Since inspection is the first and one of the most important steps of maintenance process, we can claim that these operations can determine the possible damages early, and significantly reduce the costs of repair/renewal expenses. Now, we can evaluate the cost and time spent on inspection processes in the current system.

The exact expenses that spent by the government towards inspection processes cannot be found out. However, with some reasonable assumptions, we can try to estimate these values. While doing that, we are going to use a conservative estimation approach and underestimate the actual costs. Most of the inspection cost is determined by the wage of the bridge/building inspectors. There are about 7150 buildings and 150 bridges in Toronto, which adds up to 7300 infrastructural entities [6]. At each bridge, the inspector needs to spend three hours on average on a typical site [1]. Assuming the length of bridges and height of the buildings are parallel, we also assume that an inspector must spend 3 hours on average per building. However, we can easily claim that the total time spent per entity is higher than 3 hours when transportation and reporting times are also considered. Hence, we estimate the average time spent on a site as about 5 hours. According to the data we obtained from multiple resources, the average wage of a building inspector is around $35/hr [7]. When all the parameters are multiplicated, we obtain $1,280,000 annual cost. The details of the calculations can be found in Appendix 1a. However, this is clearly a conservative estimate since it does not include cost of equipment (such as forklifts used to inspect tall buildings), safety cost of the inspectors; especially the ones that are working at high buildings or liability costs that might arise due to injuries. There are certain hidden costs such as blocking the roads to inspect a bridge as well which were not taken into consideration.

The time that must be spent towards inspection in the current system is simply the multiplication of the number of entities and average time spent per entity, which gives us 21,900 hours annually (Appendix 1b).

3. Solution Methodology

In this project, we would like to increase the efficiency of inspection processes held on buildings and bridges by mostly utilizing the time spent during these operations while reducing the expenditures. Thanks to the recent technological improvements, unmanned aerial vehicles (UAVs) became a viable option to carry out various inspection tasks in many different areas such as wind turbines, power lines, bridges, building, crops or even crime scenes [8]. Besides collecting data, these vehicles can access to difficult-to-view areas easily. Moreover, they are also a much safer option for inspecting infrastructure that are posing significant threats such as risk of collapsing. It should also be highlighted that the advancements on image capturing devices helped UAVs to be equipped with high-quality and lightweight cameras to be fixed on them in order not to miss even the slightest visual detail without hurting their flying capabilities or causing excessive battery usage because of weight handicaps. Similarly, advancements in lithium-ion battery technology make it possible to have long enough flights for adequate data collection without interruptions. All in all, these features pose UAVs as the perfect fit for inspection operations nowadays.

In the light of all this information, we propose to fly UAVs to inspect buildings and bridges. With the help of high-quality images taken, cracks or damages can be determined, which we plan to do with the image recognition model we developed, and cost and time spent on the inspections of entities that are in good condition can be completely eliminated. After eliminating the images that are free of damage, we are proposing to run a second model which determines the width of the cracks in order to be able to classify these as dangerous or not. As this stage of our model is not as advanced, inspectors can decide to inspect each crack without considering the second model. Even in this case, they are only required to inspect the buildings that has damage on them instead of going through every single entity. Now, we can estimate the cost and time of this methodology and compare it with the current system.

The cost of this solution methodology is going to be overestimated in this case, in order to be able to say that the cost of an overestimated solution is still much less than an underestimated one of the current system. To begin with, we first need to determine the number of UAVs we require.

The average height of a building in Toronto is 70m [6], and with certain assumptions (explained in Appendix 2a in detail), one side of a building can be scanned in about 15 minutes. Since the UAVs have approximately 30 min battery life [9], we need 2 UAVs to work simultaneously per building to cover all sides (We again refer to one of our previous assumptions and claim that a bridge can also be inspected at the same rate). Assuming 1 hour of transportation time for the UAV operators (since the area they are going to cover will be a compact one), they can work for 7 hours per day. In this case, 14 buildings can be covered daily by 2 UAVs. In 250 working days per year, we figure out that we need to inspect 28 buildings per day. This means that purchasing 4 UAVs will be enough (Appendix 2a). However, to be safe and overestimate, we decided to analyse purchasing 8 UAVs, assuming 1 backup UAV for each original one. For each UAV, we also propose to buy an additional battery, in order to be able to fly the vehicle with one while the other can be charged.

At this point, cost of the solution consists of three main parts as UAV cost, battery cost and operator cost. One UAV costs about $1,500; hence, we observe a cost of $12,000 [10]. Additional batteries cost around $200, so that brings in another $1,600 [11]. As we are going to operate 4 UAVs each day, we require 4 operators which will lead to 32 daily men hours. Since UAV operators require to be qualified, we assume their hourly wage is higher than \$35, and set it to \$50/hour. This results in an annual operator cost of about \$400,000. Finally, as we are still expecting the inspectors to go and analyse the cracks in the damaged sites, we should also add this cost too. According to a report filed in 2009, around 7% of the bridges were in poor condition [1]. Thus, we overestimate this rate as 10% for both bridges and buildings; and assume that the inspectors are going to spend 1 hour on average (compared to the 3 hours of before) as they know the location of the damage exactly. Considering this expense as well, we reach to an annual total cost of \$440,000 (Appendix 2b).

In terms of time spent, the solution requires the inspectors to visit only 10% of the sites in person and spend 1 hour; hence the assessment part will take only 700 hours/year. In addition, operating UAVs 32hr/day in 250 working days will bring in an additional 8,000 hours. Hence, the total time spent is around is 8,700 hours in a year (Appendix 2c).

It could be observed that, with the proposes solution method, even in the worst case, savings close to \$850,000 can be obtained. In other words, there could be a 65% decrease in the expenditures on infrastructure inspection processes. Considering the under and overestimations of current and prosed solution's cost, we can claim that the percentage decrease observed in the cost in reality will be even higher. In terms of time, we eliminate all the unnecessary inspection time spent on the sites that are actually in good condition and decrease the yearly men hours by 13,200 hours (60% decrease). By this way, we both increase the efficiency of the process and also transfer these men hours to other crucial processes such as maintenance and repairs.

In addition to the numerical gains, there are also other benefits of utilizing UAVs for building and bridge inspections. As it is mentioned, they are a much safer option to on-site inspections; especially high buildings and bridges that are posing threats. Another benefit is that UAVs can access to the areas that are difficult to reach. Last but not least, human errors can actually be reduced with the high-resolution images in terms of not missing the smallest cracks that human eye can miss.

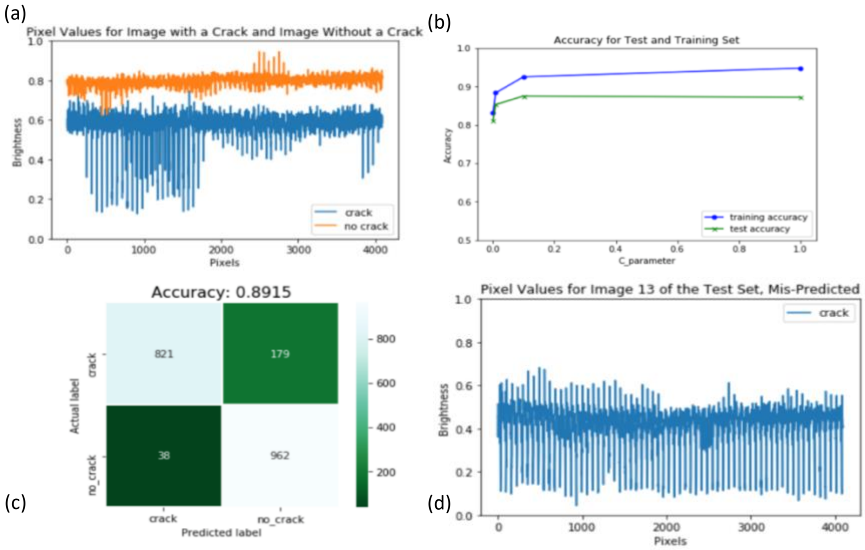
4. Model and Results

To initiate the modelling stage, first we found a dataset with 40,000 images from Mendeley [12]. Then, we developed a model that consists of two stages. In the first one, we determine if there is a crack present in the image. In the second step, we eliminate the images without a crack and for the remaining ones we try to estimate the width of the crack and categorize it as dangerous or not.

4.1 Classification of Crack/No Crack

In order to start this analysis, the data was split into two categories as images with and without a crack. Then, 8,000 images were sorted into a training set and 2,000 images sorted into the test set, achieving a 80-20 split for a total of 10,000 images used. Both sets are generated in a way that in each set exactly half of the images had a crack, so neither the training nor test set data were biased. Only 10,000 images were used to decrease time for the analysis. The images were resized to 64x64 and converted to grayscale in order to be processed. For each image, pixel brightness was extracted (a decimal number between 0 and 1) for all 4,096 pixels and stored in an array. The pixel brightness for each images' 4,096 pixels are the independent features that were loaded into the test and train sets. Whether the image had a crack or not was coded as the dependent variable, which was a 0 or 1 value. The logistic regression model was trained and then tested, and an accuracy score of 88% was achieved.

Hyperparameter tuning was conducted to determine the optimal C value ($C=1/\lambda$, where λ represents the complexity of the model) in an effort to improve the model. The optimal value was found to be 0.1, and the models accuracy improved to 89%. Of the 217 images that were incorrectly predicted, 179 were predicted to not have a crack when in reality they had. This seemed to occur because while a crack was very present to the human eye, there was no apparent section that would indicate a crack is present (as it can be seen in Figure 4; when there was a clear bulge (decrease in brightness for a subset of sequential pixel values) that would indicate a crack is present).

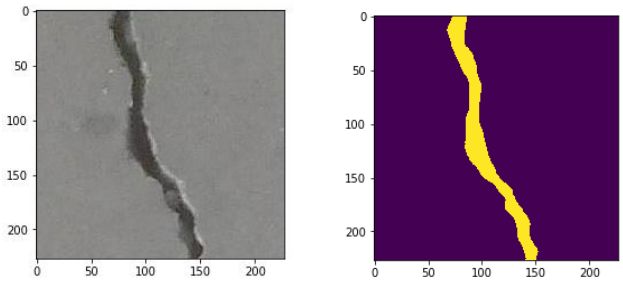


(a) Pixel values for image with and without a crack. (b) Accuracy for test and training set to determine optimal c parameter. (c) Confusion matrix of logistic regression model with optimal C value. (d) Pixel values for image that had a crack, yet the logistic regression model predicted no crack.

Figure 4: Analysis of Logistic Model Performance

4.2 Determining the Width of a Crack

As the second step of the model, the image was further processed in order to analyse the crack properties. This stage involved thresholding, noise elimination and then conversion to binary. This transformation is illustrated in Figure 5. It should be noted that this image corresponds to a numpy array. With the array, we can then calculate how much area the crack covers by comparing the non-zero pixels that correspond to the crack, to the entire area. From the array we can also analyse the horizontal and vertical dimensions of the crack. Both are measured in terms of pixels, and the direction with lesser error gave the approximate directionality of the crack, such that the width can be determined. To illustrate this, running image in Figure 5(a) through this python program yields the following: crack coverage of 6.165 of the entire image in the form of a vertical crack that is 13.99 pixels wide.



(a) (b)

Figure 5: (a) Original Image with a Crack, (b) Post-Processing Image

5. Further Advancements and Conclusion

The preliminary results obtained in this project indicate that promising results could be achieved by further enhancements. For the first part of the model, the predictions could be improved by using a Convolutional Neural Network (CNN), a deep learning model. While the CNN was considered for use in the initial analysis, the model requires significantly large amount of times; however, its prediction capabilities may be much stronger, when the model is trained properly. For the second stage of our modelling, it is observed that the irregular brightness in the images causes some error. At times, a dark smudge or spot will be counted as part of the crack, and at other times, thin crack sections will be omitted. A methodology would have to be established in taking the pictures to alleviate this error; hence, the model can be developed in this manner. However, despite not having the listed improvements, this study is still showing lots of merit in terms of cost/time savings and high-quality model results.

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Appendix

Appendix 1a: Annual Cost of Current Inspection System

$$\begin{aligned}\begin{matrix}\text{Annual Cost}\\\text{of Inspection}\end{matrix} &= \begin{pmatrix}\text{\# of infrastructed}\\\text{entities}\end{pmatrix} \times \begin{pmatrix}\text{total \# of hours}\\\text{required to be spent}\\\text{for one inspection}\end{pmatrix} \times \begin{pmatrix}\text{wage of inspector}\\\text{(per hour)}\end{pmatrix}\\ &= (7151+138) \times 5 \times \$35\\ &= \$1,275,575.00\end{aligned}$$

Appendix 1b: Annual Time of Current Inspection System

$$\begin{aligned}\begin{matrix}\text{Annual Time}\\\text{of Inspection}\end{matrix} &= \begin{pmatrix}\text{\# of infrastructed}\\\text{entities}\end{pmatrix} \times \begin{pmatrix}\text{total on-site inspection}\\\text{hours per entity}\end{pmatrix}\\ &= (7151+138) \times 3\\ &= 21,867 \text{ hours}\end{aligned}$$

Appendix 2a: Number of Drones Required in Proposed Inspection System

$$\begin{aligned}\begin{matrix}\text{Total Building}\\\text{Height}\end{matrix} &= \begin{pmatrix}\text{\# of low-rise}\\\text{buildings}\end{pmatrix} \times \begin{pmatrix}\text{avg height}\\\text{of a LRB}\end{pmatrix} + \begin{pmatrix}\text{\# of high-rise}\\\text{buildings}\end{pmatrix} \times \begin{pmatrix}\text{avg height}\\\text{of a HRB}\end{pmatrix} + \begin{pmatrix}\text{\# of sky-}\\\text{scrapers}\end{pmatrix} \times \begin{pmatrix}\text{avg height}\\\text{of a SS}\end{pmatrix}\\ &= 4242 \times 30 + 2630 \times 80 + 645 \times 250\\ &= 498,910 \text{ meters}\end{aligned}$$

$$\text{Avg Building Height} = \frac{498,910}{7,151} = 69.8\text{meters}$$

Assume images are 1mx1m, average width of a building is 12m and each image is taken in 1 second.

UAV Time/Building/Side = 70 x 12 x 1 = 840 sec = 14min

UAV flight time = 30 min → With 2 simultaneous UAVs, 4 sides of a building can be inspected in 30 min.

$$\text{Number of Entities to Inspect/Day} = \frac{7,289}{250} = 28 \text{ entities/day}$$

$$\text{Number of Entities Inspected with 2 UAVs} = 7\times0.5 = 14 \text{ entities/day}$$

Hence, in order to be able to inspect 28 entities in a day, 4 UAVs are required.

Appendix 2b: Annual Cost of Proposed Inspection System

$$\begin{aligned}\begin{matrix}\text{Annual Cost of}\\\text{UAV Solution}\end{matrix} &= \begin{pmatrix}\text{\# of UAVs}\\\text{(with bakcup)}\end{pmatrix} \times \begin{pmatrix}\text{cost of}\\\text{an UAV}\end{pmatrix} + \begin{pmatrix}\text{\# of extra}\\\text{batteries}\end{pmatrix} \times \begin{pmatrix}\text{cost of a}\\\text{battery}\end{pmatrix} + \begin{pmatrix}\text{\# of days}\\\text{/year}\end{pmatrix} \times \begin{pmatrix}\text{\# of men-}\\\text{hours/day}\end{pmatrix} \times \begin{pmatrix}\text{wage of an}\\\text{operator/day}\end{pmatrix}\\ &= 4+4 \times \$1,500 + 8 \times \$200 + 250 \times 32 \times \$50\\ &+ \begin{pmatrix}\text{\# of}\\\text{entities}\end{pmatrix} \times \begin{pmatrix}\text{damage}\\\text{rate}\end{pmatrix} \times \begin{pmatrix}\text{\# of hours spent}\\\text{on inspection}\end{pmatrix} \times \begin{pmatrix}\text{wage of an}\\\text{inspector/day}\end{pmatrix} = \$439,111.50\\ &+ 7289 \times 10\% \times 1 \times 35\end{aligned}$$

Appendix 2c: Annual Time of Proposed Inspection System

$$\begin{aligned}\begin{matrix}\text{Annual Time of}\\\text{UAV Solution}\end{matrix} &= \begin{pmatrix}\text{\# of days}\\\text{/year}\end{pmatrix} \times \begin{pmatrix}\text{\# of men-}\\\text{hours/day}\end{pmatrix} + \begin{pmatrix}\text{\# of}\\\text{entities}\end{pmatrix} \times \begin{pmatrix}\text{damage}\\\text{rate}\end{pmatrix} \times \begin{pmatrix}\text{\# of hours spent}\\\text{on inspection}\end{pmatrix}\\ &= 250 \times 32 + 7289 \times 10\% \times 1\\ &= 8728.9 \text{ hours}\end{aligned}$$