2023 Spring Urban Sensing Final-Project

Pigeon Among Us
A study on how pigeons live their lives in urban areas

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Abstract

Urban pigeons are a common sight in many cities around the world. Despite their ubiquity, relatively little is known about their behavior in urban environments. This study aimed to observe and document the behavior of urban pigeons in a condensed downtown park setting, with a focus on their behavioral patterns and interactions with citizens. Pigeons were observed and recorded using a combination of video and written notes. This project adapted computer vision methods to detect and track pigeons and inferential analysis was performed based on the results. Findings of the study showed that pigeons spent a significant amount of time engaged in feeding behavior. The pigeons also exhibited a zig-zag pattern of approaching sitters for food. In addition, the study documented several instances of human-pigeon interaction, including feeding by park visitors and occasional aggressive behavior towards the birds. The study concludes that urban pigeons are highly adaptable and able to thrive in a variety of urban environments, but also highlights the need for further research on the potential impact of human activity on their behavior and mutual wellbeing.

Introduction

Background

As one of the most abundant and widespread species on the planet, pigeons are managing to thrive in chaotic cities. They owe their success to an ideal combination of traits, including a low bar for homemaking and fast reproduction. Pigeons' population in the city is also accentuated by humans and the city environment. They take advantage of urban food waste on the ground or in the trash cans as well as people's feeding. New York City, as a perfect environment for them, is home to over a million pigeons. The species found in NYC is the rock dove. Their liabilities are further strengthened because the city's tall buildings and infrastructure serve as a perfect alternative to a rock dove's natural habitat on the sides of cliffs.

Problem Statement

While pigeons play a starring role in urban wildlife, they are not always welcoming neighbors. Excessive pigeon activities in urban areas have raised sanitary problems: pigeons are known to be carriers of several diseases, such as salmonellosis and cryptococcosis, which can be transmitted to humans through contact with bird droppings or other materials contaminated by pigeons. Although the pigeons are notoriously known as the "flying rat", some urban residents maintain a close relationship with the pigeons by feeding them, observing them, and getting close to them. Some pigeons just walk freely among passengers, and some may know when and where to go food hunting.

As an urban dweller since the 1600s, the pigeons have long adapted to the urban environment, thriving on available food sources and utilizing buildings for roosting and nesting. Understanding urban pigeon behavior is essential for mitigating the hygiene issue and promoting coexistence between humans and pigeons. Therefore, this project aims to focus on the pigeons' living behavior as well as their interactions with citizens in condensed New York City parks to see how they influence urban life.

Related Works

Urban pigeons are a common sight in cities worldwide, often inhabiting public spaces, rooftops, parks or even buildings' balconies. Traditionally, studies on urban pigeons have focused on ethological observations, field surveys and tagging techniques. While these methods have valuable insights, they are often time-consuming, limited in scope, and require intensive manual labor. With advancements in computer vision technology, researchers have turned to automated video analysis as a promising approach to study animal behavior. Looking into recent studies related to pigeons using CV, many of them only focused on detection of pigeons rather than analysis of their behaviors. Study conducted by Schiano et al. introduces an autonomous pigeon avoidance system that combines computer vision and drones to detect and deter pigeons from roosting on buildings. Camera on the drone was used because of the hardware advantage when performing computer vision as it could move through the environment to search for pigeons. By applying convolutional neural networks (R-CNN) on real-time video and camera images, the study was able to predict bounding boxes with class and coordinates based on a pre-trained model with ImageNet and MSCOCO datasets. The model was then fine-tuned with specifically collected images of pigeons in an urban environment and was trained to distinguish between two different classes (pigeons and other) by manually labeling the false positive for better performance.(Schiano et al. 2021)

While there is limited literature specifically analyzing pigeon behavior, the utilization of computer vision for analyzing animal behavior is not uncommon. Research led by Marks et al. presents a comprehensive system utilizing deep learning techniques to analyze the behavior of primates and mice in complex environments directly from raw video frames captured by mono-vision cameras. The study created a behavior classifier that performs segmentation, identification, pose-estimation and classification based on a supervised model trained with annotated snippets of video footage of mouse behavior.(Marks et al. 2022) Another study conducted by Sun et al. also develops a strategy to track the movement of mice by applying a deep learning technique, the You Only Look Once (YOLO) algorithm on videos of moving animals. Since YOLO only provides the position of an area around the animal (bounding box) instead of the actual position of the animal, the study incorporated a background subtraction algorithm to obtain the contour of the animal in the bounding box and infer the movement based on the centroid calculated from the contour. (Sun et al. 2021)

Research Questions

Above studies used computer vision on tracking and analyzing the movement pattern of animals, yet they were only applied in a relatively controlled lab environment. We were wondering if the same methodology could be applied to pigeons in public areas with more complex environments and noise. Therefore, the project aims to answer the following questions:

1. What are the characteristics of pigeons' living environment in urban areas; how do they correlate with pigeons' life style?
2. How does pigeons' movement pattern change when interacting with the surrounding environment?

In order to answer the research questions, the project will be separated into two parts using video and image data respectively. Images are used to answer the first question by counting the number of pigeons and other elements around them, aiming to identify any commonalities and correlations. Videos are used to answer the second question by drawing the moving path of the pigeons to see if there is any specific pattern that could be categorized based on the different surrounding environment.

Methodology

Data Collection

The original location was set to Grove Street Path station and Union Square Park, however due to the events held at Grove Street, only a few data was collected at Grove Street Path Station, so we added Washington Square Park as our third observation spot. The final data collection was performed at Washington Square Park, Union Square Park and Grove Street Path Station. Data was collected on April 28th and April 29th from 11am to 1pm and 2pm to 5pm. Videos and pictures were taken using iPhone 14 Pro back cameras. The initial idea was to set up a GoPro on a tree or using a tripod, but the zoomed out view was not ideal for object detection and tracking. A total of 50 photos and 125 videos were collected.

Video Data processing

Python was used for data processing and analysis, the main algorithm for pigeon detection and tracking in videos was YOLOv3. YOLOv3 (You Only Look Once version 3) is a real-time object detection algorithm, it is a deep neural network that can detect and classify objects in images and videos with high accuracy and speed. YOLOv3 uses a single neural network that takes the entire image as input and divides it into a grid. Each cell in the grid predicts a set of bounding boxes and their corresponding confidence scores, as well as the class probabilities for each box. YOLOv3 has been trained on a large dataset of images and can detect a wide range of objects, including people, animals, vehicles, and household items. We chose YOLOv3 as our final model for video processing due to the accessibility of the pre-trained models and ease of usage.

Step 1: Videos recorded were filtered first. Since the locations were crowded, videos with consistently blocked target objects were removed. 89 videos were selected for data processing.

Step 2: Videos were trimmed into smaller chunks for faster and more consistent processing. This also helped with the main camera view movement since sometimes the pigeons are out of sight so we had to adjust the view of the camera.

Step 3: The prepared videos were fed into a pre-trained YOLOv3 model(Olafenwa 2022). The model returned the videos with tracked frames. The per_frame_function was set to return the list of centroids of the detected birds per frame and a list of the number of birds detected per frame.

Below shows the model specifications:

```
frames_per_second=20
log_progress=True
per_frame_function=on_frame
return_detected_frame=True
frame_detection_interval=10
```

Video Data analysis

Since the algorithm cannot keep track and differentiate different birds from frame to frame, we implemented k-means clustering to group the output data. The number of birds identified would be the number of clusters for the model.

For each video, we first took the maximum bird count in the count list. If the maximum count was one, we set the number of birds to 1; if the maximum count was greater than 1, we set the number of birds to the mode of the count list to compensate for the cost of detection errors.

Step 1: Fit the K-means clustering model and return the coordinates of different birds.

Step 2: Plot the trajectory based on the clustered data, with different colors representing different pigeons. The plots were saved into a folder for results interpretation.

Image Data Processing

Similar to the video data, python was used for data processing and analysis, but the algorithm used for the image detection was YOLOv8. The basic logic of the model is the same as YOLOv3, except that YOLOv8 builds upon the success of previous YOLO versions, aiming to improve accuracy and speed in real-time object detection tasks. YOLOv8 has the detection, segmentation, pose and classification model. Our project chose to use a detection model that is pre-trained on the COCO dataset to detect objects in the image. We've tried YOLOv3 and YOLOv5, but the detection results weren't as accurate as YOLOv8 as it couldn't identify the correct number of pigeons if they were clustered together or the contrast ratio of the image was too low.

Step 1: Photos taken were filtered first. We were interested in the surrounding environment of pigeons' habitat, we only kept photos with pigeons with clear indication of surroundings. 43 photos were selected for data processing.

Step 2: The photos were fed into a pre-trained YOLOv8x model. The model returned photos with bounding boxes of detected objects and corresponding probabilities. By setting the parameter "save_txt=True", it will also return a text file with the class name of each detected object and their bounding box coordinates.

Step 3: Based on the text files, we count the number of objects in each photo and write it as a row to a new text file such as "3 bird, 2 person, 2 backpack".

Image Data Analysis

For a better analysis of the data, we converted the text file into a dataframe in a fixed schema with each row representing a photo and each column representing the unique object detected. If the object doesn't exist in that photo, the code will automatically fill in 0 for that row.

In order to see the relationship between pigeons and elements in surrounding environments, we choose to perform linear regression on the dataframe. Y would be the number of pigeons and X would be the rest of the columns. We could find positive/negative relationships from the coefficients. A correlation matrix heatmap plot would be drawn for better understanding through visualization.

Based on the p-value of each column we got from the regression, we will consider whether to perform principal component analysis to reduce noise by eliminating multi-collinearity between features.

Results

We processed all videos and photos and based on the quality and interpretability, we selected some sample results of relatively stable camera views' videos.

Results Comparison

To see the accuracy of using YOLOv3 for pigeon detection, we also manually counted the number of pigeons in the videos we were interested in tracking. Table 1 shows the manual counted result and Table 2 shows the summary data of pigeons detected using computer vision.

Number of Pigeons of Interest	Count	Percentage
1	28	33.7%
2	22	26.5%
3	7	8.4%
3+	26	31.4%

Table 1: Manual Count Result

Number of Pigeons Detected	Count	Percentage
1	42	50.6%
2	24	28.9%
3	13	15.7%
4	1	1.2%
5	1	1.2%
6	1	1.2%
9	1	1.2%

Table 2: YOLOv3 Count Result

Image Data Result

The YOLOv8x model has detected 23 unique objects from 43 selected photos that contain pigeons we took randomly in Washington Square Park and Union Square. Table 3 shows the descriptive statistics of the detection results. We could see that people indeed have the highest occurrence near pigeons, followed by bench, backpack, car and cell phone. Figure 1 shows an example of the object detected with the bounding box and the probability. The detection result is quite accurate compared to the actual photo except for some rare errors such as misclassifying a pigeon to a dog. Setting the probability benchmark to 0.3 could help to mitigate the issue. However, since the pre-trained model has limited variety of the object classes, many other objects that we are interested in could not be identified, such as the trash bin, food cart and larger surrounding greenbelt or trees.

Knowing that pigeons will usually stay near people or benches, we are wondering whether there is some correlation between the number of pigeons and the surrounding environment. Do pigeons usually gather in a group or just act individually in the public? A correlation matrix was created based on Pearson's r. From the Table 4, we could see that almost all the object classes are negatively correlated with the number of pigeons. Taking p value < 0.05, the number of people is statistically significant to the pigeons. Combining the result with our observation from the photo, pigeons' living behaviors can be separated into two ways. Pigeons tend to gather together in groups of ten or more on the lawn with fewer people and objects around. They are more likely to be at rest or sleeping in relatively open spaces as figure 2(a) shown. However, most of the time, when they need to

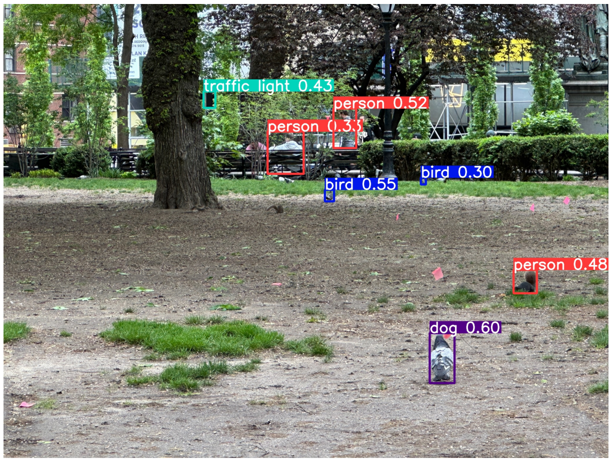


Figure 1: YOLOv8 Image Data Analysis

find food, they will split into small groups with two or three and fly into areas with more human presence, often circling around benches or trash bins in figure 2(b).

A linear regression model was also fitted to the data with the dependent variable being the number of pigeons and independent variables being the number of each unique object detected. Figure 3 shows the result. However, although the OLS regression model shows the negative correlation of objects with the number of pigeons, all of them have extremely high p-value, which means that there might be high multicollinearity between features such as backpack and people, dining table and chair that need further model tuning and more sampling data.

Figure 2 show some sample results of image data detection using YOLOv8.

Video Data Result

Figures in later pages show some typical scenarios we observed, examples from different locations are shown.

Figure 4 shows a sample plotted path of the pigeons detected. The video of figure was taken in Washington Square Park when two pigeons were walking across passengers. We can see that the plotted path is relatively long and zig-zaged.

Figure 5 show another pattern of 4 pigeons feeding on a relatively empty streetside near Grove Street Path Station. The plotted trajectories showed relatively short and narrow movement range.

Figure 6 shows a pigeon trying to stay away from the passenger with luggage. The path reflected the pigeon was walking fast straight.

Figure 7 shows the trajectory of two pigeons, the left one was approaching the sitters for food and the right one was trying to avoid a scooter. It was interesting to notice that the right bird at this frame was misclassified as a skateboard.

Figure 8 shows the trajectory of two pigeons feeding on themselves in a relatively empty path with no passengers in Union Square Park. The plotted trajectories showed a compacted zig-zaged pattern.

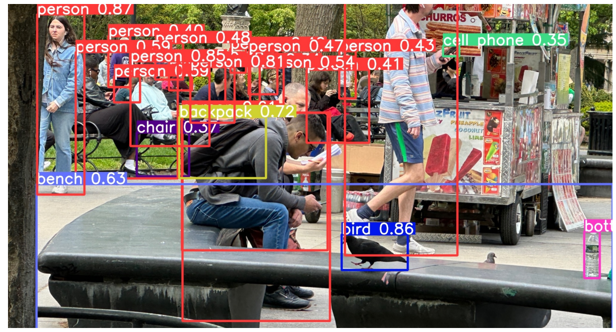
Table 3: Descriptive Statistics

	Valid	Mean	Maximum	Sum
bird	43	6.977	28.000	300.000
person	43	9.233	24.000	397.000
bench	43	2.070	9.000	89.000
bottle	43	0.209	5.000	9.000
handbag	43	0.256	4.000	11.000
frisbee	43	0.023	1.000	1.000
traffic_light	43	0.116	3.000	5.000
bowl	43	0.023	1.000	1.000
backpack	43	0.326	2.000	14.000
cell_phone	43	0.256	3.000	11.000
cup	43	0.093	2.000	4.000
boat	43	0.023	1.000	1.000
fire_hydrant	43	0.023	1.000	1.000
dining_table	43	0.116	2.000	5.000
sandwich	43	0.047	1.000	2.000
dog	43	0.023	1.000	1.000
umbrella	43	0.140	2.000	6.000
car	43	0.279	3.000	12.000
bicycle	43	0.023	1.000	1.000
chair	43	0.093	1.000	4.000
truck	43	0.186	2.000	8.000
motorcycle	43	0.023	1.000	1.000
book	43	0.023	1.000	1.000

Table 4: Pearson's Correlations

			Pearson's r	p
bird	-	frisbee	-0.154	0.324
	-	traffic_light	0.008	0.962
	-	person*	-0.339	0.026
	-	book	5.136×10^{-4}	0.997
	-	backpack	-0.295	0.055
	-	handbag	-0.119	0.446
	-	cell_phone	-0.258	0.094
	-	bottle	-0.205	0.188
	-	cup	-0.229	0.139
	-	boat	-0.022	0.891
	-	fire_hydrant	-0.022	0.891
	-	dining_table	-0.257	0.096
	-	sandwich	-0.110	0.483
	-	dog	-0.110	0.483
	-	umbrella	-0.186	0.231
	-	car	-0.152	0.329
	-	bicycle	-0.132	0.399
	-	bench	-0.220	0.155
	-	chair	-0.274	0.075
	-	truck	-0.059	0.705
	-	motorcycle	-0.132	0.399
	-	bowl	0.045	0.776

(a) Pigeons Resting in Group



(b) Pigeon looking for food

Figure 2: YOLOv8 Image Data Analysis

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   bird   R-squared:                       0.429
Model:                            OLS   Adj. R-squared:                 -0.090
Method:                 Least Squares   F-statistic:                    0.8274
Date:                Sat, 13 May 2023   Prob (F-statistic):              0.663
Time:                        01:19:43   Log-Likelihood:                -132.55
No. Observations:                  43   AIC:                             307.1
Df Residuals:                      22   BIC:                             344.1
Df Model:                          20
Covariance Type:            nonrobust
=================================================================================
                    coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------
const            13.5703      2.542      5.337      0.000       8.297      18.843
frisbee         -12.6595     13.174     -0.961      0.347     -39.981      14.662
traffic_light    -0.7610      3.051     -0.249      0.805      -7.089       5.567
bowl             -1.3912      8.485     -0.164      0.871     -18.988      16.205
book            -17.4439     21.224     -0.822      0.420     -61.460      26.572
backpack          1.3457      4.321      0.311      0.758      -7.616      10.307
handbag           9.0584      7.488      1.210      0.239      -6.470      24.587
cell_phone       -9.1306      5.305     -1.721      0.099     -20.132       1.870
bottle            4.0222      3.460      1.163      0.257      -3.153      11.197
cup              -0.0271      7.585     -0.004      0.997     -15.758      15.703
boat             -7.4239      5.322     -1.395      0.177     -18.461       3.613
fire_hydrant     -7.4239      5.322     -1.395      0.177     -18.461       3.613
dining_table     -6.5427      6.058     -1.080      0.292     -19.107       6.022
sandwich         -7.8827     11.092     -0.711      0.485     -30.885      15.120
dog             -10.1321      8.085     -1.253      0.223     -26.900       6.635
umbrella          0.6624      4.139      0.160      0.874      -7.921       9.245
person           -0.2257      0.345     -0.654      0.520      -0.941       0.490
car              -1.6154      1.966     -0.822      0.420      -5.693       2.462
bicycle           3.7701      6.112      0.617      0.544      -8.906      16.447
bench            -0.8780      0.791     -1.110      0.279      -2.518       0.762
chair            -6.0751      5.079     -1.196      0.244     -16.608       4.458
truck            -3.6217      3.357     -1.079      0.292     -10.583       3.340
motorcycle        3.7701      6.112      0.617      0.544      -8.906      16.447
==============================================================================
Omnibus:                        8.920   Durbin-Watson:                   2.159
Prob(Omnibus):                  0.012   Jarque-Bera (JB):                8.203
Skew:                           0.843   Prob(JB):                       0.0165
Kurtosis:                       4.317   Cond. No.                     1.67e+18
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 2.17e-33. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
```

Figure 3: OLS Regression Result

Aggressive Behaviors

Figure 9 (on last page) show some caught-in-action aggression towards the pigeons.

Feeding pigeons

Figure 10 and figure 11 (on last page) show some activities of feeding pigeons.

Conclusion

We were able to find most urban pigeons in groups rather than alone. We didn't see urban pigeons purposely avoiding humans unless potential threats from their belongings or behaviors were noticed. They tend to be rested in the open areas with fewer people but most of the time they will go hunting for food in pairs actively around people or along benches. Pigeons' traveling patterns were affected by their surroundings and their own actions. For example when pigeons were trying to walk across the crowds, they tended to walk fast and smoothly detoured among passengers. When the pigeons were feeding with no one passing by, they walked around in very small steps and range.

It was expected that YOLOv3 may not perform well in pigeon detection and tracking. The algorithm was not able to differentiate and kept track of different pigeons and it was having a hard time detecting pigeons further apart in the view. YOLOv8, in comparison, performed much more detailed-oriented and accurate detection. However, running YOLOv8 on our videos was very time consuming. We also noticed that YOLOv3 did not performed well at detecting flying pigeons since none of the flying pigeons in our videos was recognized.

We also observed aggression towards pigeons but they are on very rare occasions. One of the aggressive behaviors was a kid chasing the pigeons for fun, while the others were simply driving the pigeons away. Aggression happened less than we thought, this may be because citizens are really used to pigeons in the living environment. More feeding activities were observed compared to aggressive behaviors, and pigeons would continuously fly to the feeding point from the trees.

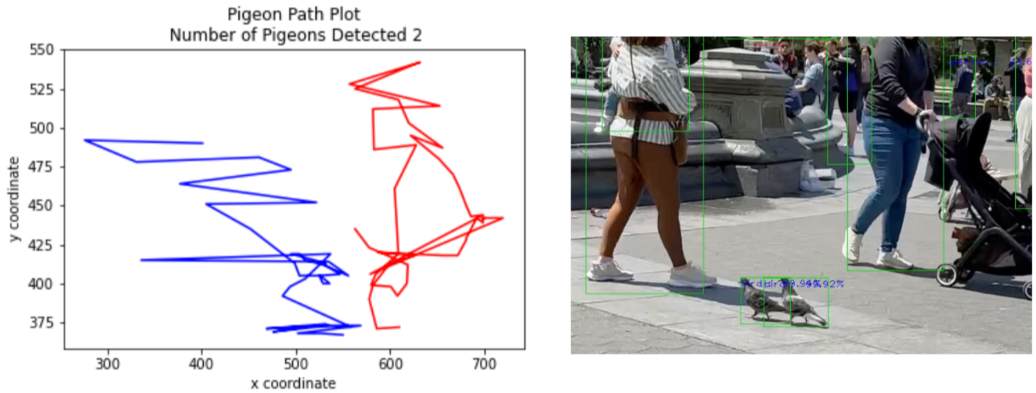


Figure 4: Pigeons walking across passengers in Washington Square Park (left: plotted path; right: detected objects in a sample video frame)

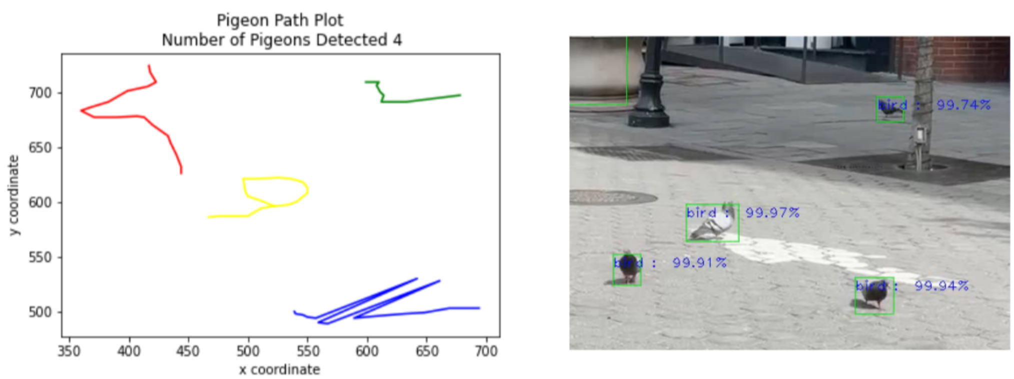


Figure 5: Pigeons feeding on a relatively empty streetside near Grove Street Path Station (left: plotted path; right: detected objects in a sample video frame)

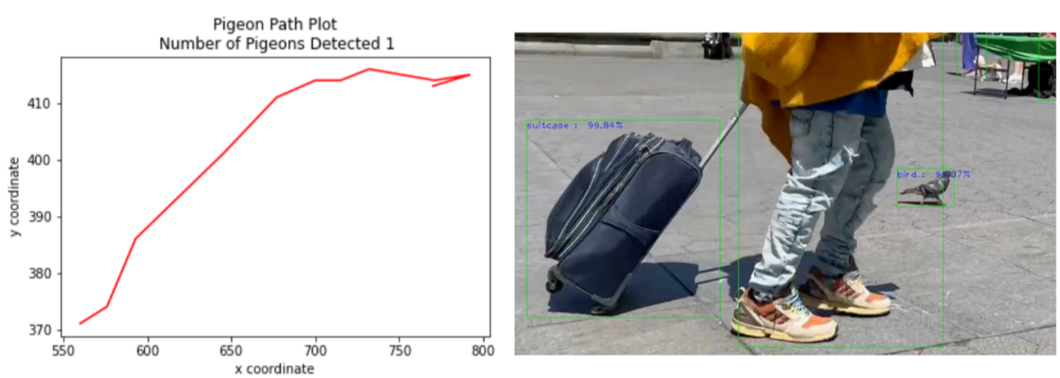


Figure 6: Pigeon trying to stay away from the luggage along the way in Washington Square Park (left: plotted path; right: detected objects in a sample video frame)

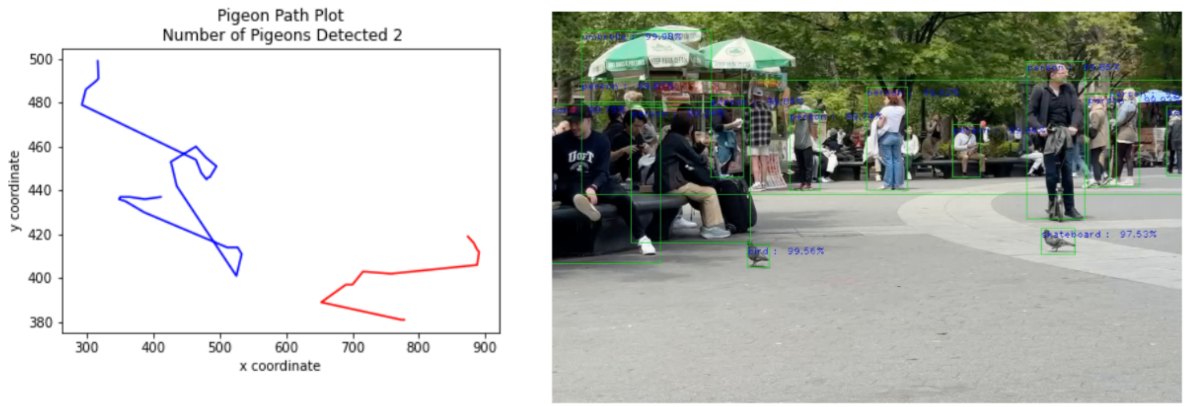


Figure 7: Left pigeon looking for food while right pigeon trying to avoid a scooter in Washington Square Park (left: plotted path; right: detected objects in a sample video frame)

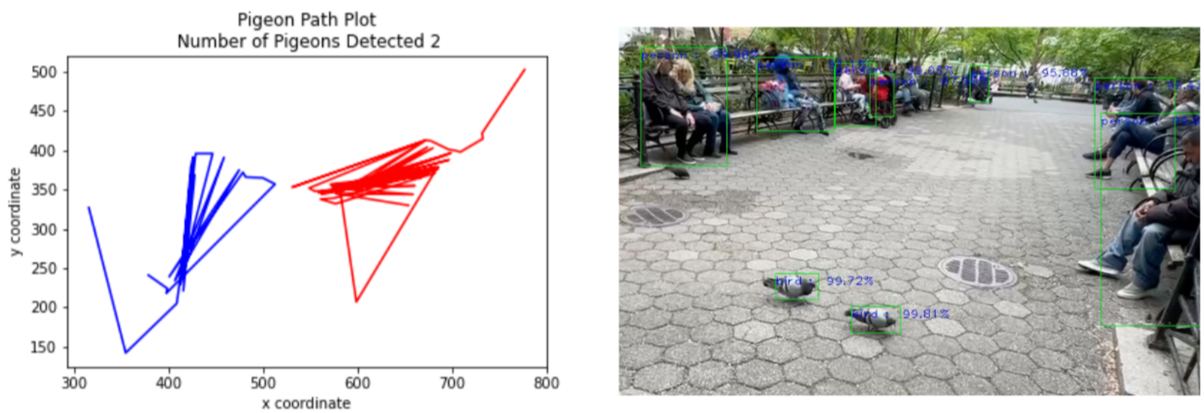


Figure 8: Two pigeons feeding on themselves in a relatively empty path in Union Square Park (left: plotted path; right: detected objects in a sample video frame)

Discussions

Pigeons are considered gregarious animals, which means they tend to live and move in groups or flocks. From our manual observing and counting results, we can see that the majority of pigeons go in pairs or groups. It was also interesting to notice that there were a decent amount of paired pigeons, which may be due to the fact that it's mating season and according to Birdwatching Buzz (Reed 2020), paired pigeons work together in finding food, raising young, and defending the nest, which increases the odds of their offspring surviving to adulthood. This project generated many interesting findings in terms of urban pigeons' behavior and their interactions with citizens, but the results and methodology can be greatly improved if below limitations were taken into consideration.

Limitations

- Limited field of view: Cameras have a limited field of view, and it can be challenging to capture the entire traveling path of a bird in a single frame. This can make it difficult to accurately track the bird's movement over time.
- Stability of camera: Camera stability is an important factor in tracking bird movements accurately. The camera was not stable since we were filming using our phones, it caused jittery footage and made it difficult to track the movement of birds smoothly.
- Accuracy in detecting and tracking flocks of birds moving: Computer vision algorithms can sometimes struggle to accurately detect flocks of birds moving together. This is because flocks can often be very dynamic, with birds constantly changing position and direction. Additionally, flocks can sometimes overlap or intermingle with each other, making it difficult for algorithms to distinguish between individual birds and groups of birds. This can lead to errors in tracking, particularly when multiple flocks are present in the same area.
- Limitations of detection range: Depending on the camera and detection algorithm used, there may be a limitation on the distance at which birds can be detected. This can be especially limiting for small or distant birds, which

may not be detected at all. Additionally, detection range can be affected by environmental factors such as lighting conditions, weather, and camera angles, all of which can further limit the accuracy of tracking.

- Lack of image and video data: Since there was limited time in collecting the data, our result may not be generalizable to all the pigeon activities in urban areas. It might be difficult to classify the behaviors of pigeons based on our data. Also, the correlation between the number of pigeons and other objects will be more obvious if we could incorporate more images for training the regression model.

Future Work and Challenges

- To tackle instability of camera view, using a mounted camera such as a CCTV monitor that can capture high quality video would be best for our case. We can then divide the high quality videos into smaller grids to perform analysis and gather results.
- Since pigeons look alike, it would be challenging to keep track of individual pigeons in flocks. There is research on human tracking by implementing YOLOv3 with DeepSort algorithm. This algorithm may provide some insights for bird tracking, but still challenging since pigeons look alike and there hasn't been documentation of applying this method on birds. If this is possible, we won't need to infer the data points for each pigeon. Also, we could use segmentation to capture the body of the pigeon instead of the bounding box to be more accurate.
- Fine tuning the model by providing customized pigeon datasets, this would boost the model's accuracy at detecting pigeons, but this requires a lot of training and data preparation. Since YOLOv3 is a relatively earlier generation model in object detection, other models such as YOLOv8, YOLOv5 are worth trying for optimal results. Also, fine tuning the regression model by performing principal component analysis to reduce noise by eliminating multicollinearity between features.
- Perform observations on different weather conditions and different urban locations. This would help us better understand how urban pigeons interact with city dwellers.
- Adapt video stabilizing algorithm to stabilize the videos, maybe using reference objects in the backgrounds would help.
- If tracking algorithm and stability are improved, it would be best to track human and pigeons at the same time to plot their paths and infer interaction patterns.

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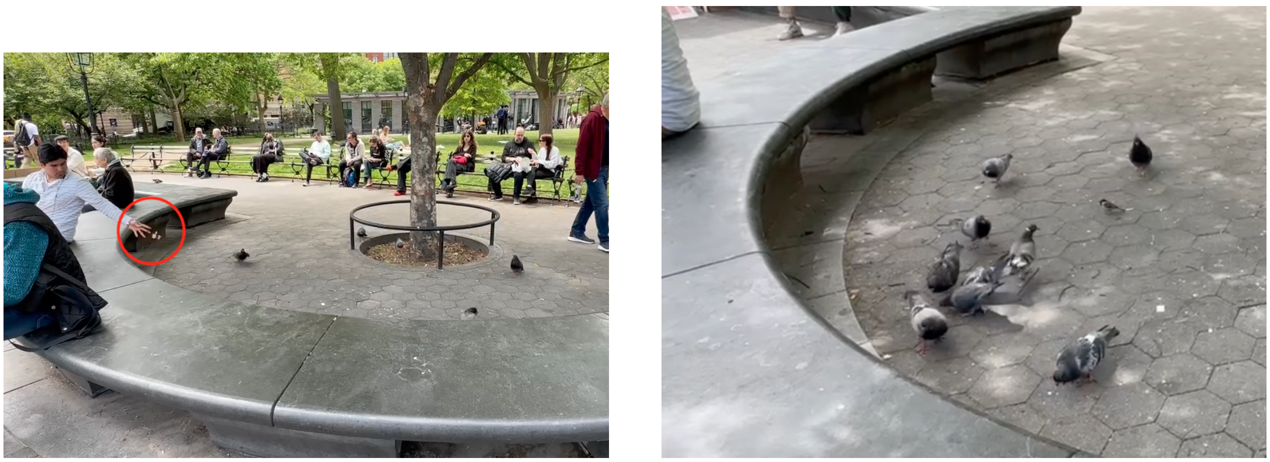
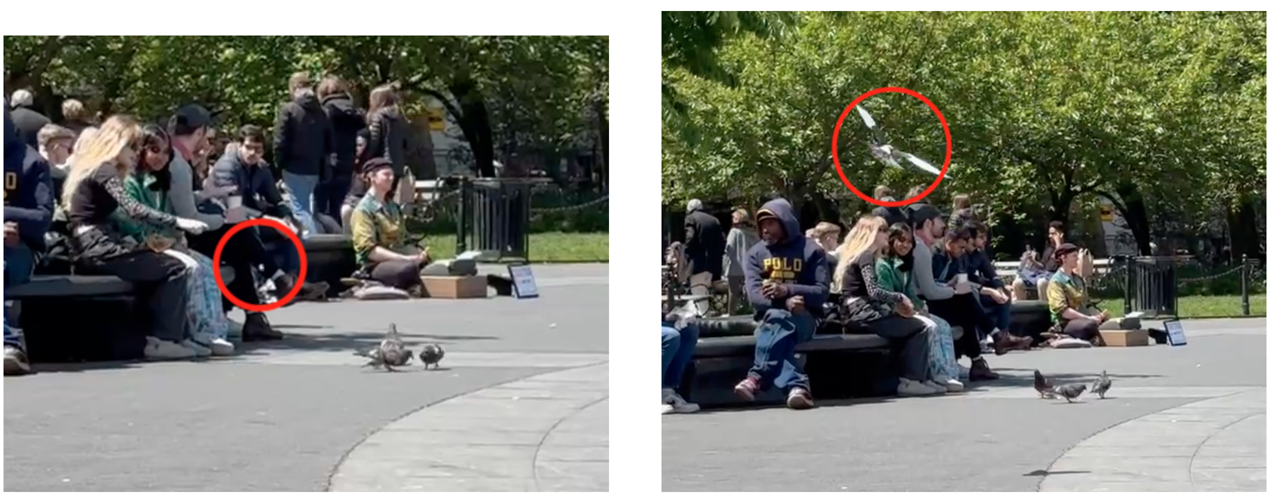
(a) Aggression 1 (b) Aggression 2

Figure 9: Aggression towards pigeons



(a) Feeding (b) Pigeons gathered after feeding

Figure 10: Feeding pigeon in Washington Square Park



(a) Feeding (b) Pigeons flying over after feeding

Figure 11: Feeding pigeon in Washington Square Park