Automated Trash Detection using Computer Vision

CIS 515 / Team C2

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INTRODUCTION

Problem to solve

Littering is a major problem faced in ASU, and manually searching for litter can be a time-consuming and labor-intensive task. This project aims to develop a computer vision system that can detect litter on the ASU campus automatically. The system could also be used to generate insights on garbage generation patterns and inform policies to reduce waste generation. We need to collect images of key locations on the campus to capture images of litter. The images are then processed using computer vision algorithms to detect and localize the litter.

Stakeholders and Beneficiaries

Tempe Community

Beneficiary

Faculty Members

Beneficiary

ASU

Stakeholder

Students

Beneficiary

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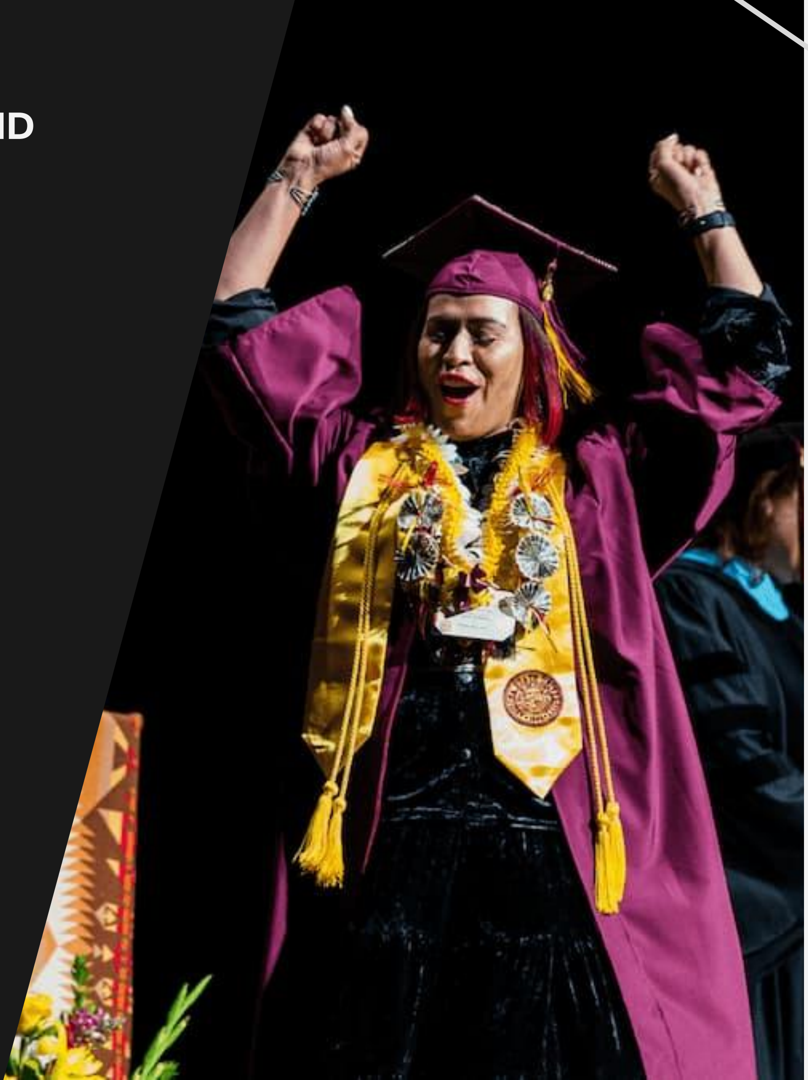
OVERALL END-TO-END SOLUTION

END-TO-END
SOLUTION



STATUS QUO

We assume that this problem is currently being solved by maintenance personnel roaming the campus to check for littering; they will then clean up the area as needed

END-TO-END SOLUTION

DATA COLLECTION

1) Determine locations on campus with the most pedestrian activity

2) Install cameras in these locations around the ASU Campus

DATA PROCESSING

4) upload trash data from installed cameras to a server, run a CV model on the data. If CV model detects a garbage,

5) send a notification to a "garbage detection" app that maintenance personnel installs on their phones.

THE END GOAL

6) The app would provide information about the location and type of garbage detected. The app will notify maintenance staff accordingly. Proper trash removal/sanitation will then be executed

SOLUTION METRICS

Value of this Solution:

- Importance of taking care of environment and limiting harm to animals/humans
- Ensure a clean campus that is enjoyable for the community
- Limit air/water pollution

Success Metric:

- Correctly detecting garbage items

Resources Required

- Gather a team of IT professionals to install CV models

- Estimating cost of implementation to be $20,000 (cameras, software, PCs, computational, storage costs)

POST DEPLOYMENT OF SOLUTION

- **Validating the trash detection pre and post deployment?**

  Conduct extensive testing to ensure the solution detects trash accurately.
  Define performance metrics to evaluate the solution's effectiveness.
  Gather users feedback to identify any issues or improvements.

- **Monitoring the solution post-deployment?**

  Continuously collect data to improve the solution's performance.
  Re-train the machine learning model based on new data to improve the accuracy.
  Regularly evaluate the solution's performance using defined performance metrics.
  Perform regular maintenance and determine if updates are necessary.

- **Potential Issues**

Image privacy Trash detection computer vision systems typically capture and process images which can include people, vehicles, and other objects
Data security the data should be protected from unauthorized access
Compliance data storage needs to be within the privacy and security regulations

SIMILAR SOLUTION IN ASU

“NEW WASTE-SORTING MACHINE BEGINS TRIAL AT MU”

• The Oscar Sort, an AI-powered machine, will help identify where different types of waste should go

• Sustainability ambassadors at the Student Pavilion, in partnership with Zero Waste.

PROBLEM

It is hard to get students , visitors, staff and faculty to sort their items when they get to the bin.

INCENTIVE MECHANISM

Educating people about types of trash

SIMILAR END GOAL

expanding scope, domains, and scenarios, using a multi-sensor approach, and leveraging artificial intelligence. The scalability of the solution depends on the resources available and the specific needs of the campus or community.

https://www.statepress.com/article/2021/03/spbiztech-asu-brings-new-waste-sorting-machine-to-campus

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COMPUTER VISION MODEL

WHY CV ADAPTION

- **We are using an existing tensorflow open cv model.**

The tensor flow models repository on github uses opencv for the purpose of image manipulation and visualization. Specifically in our case we are using it to draw bounded boxes and labels on images to display the result of object detection.

- **Alternative solutions instead of using CV**

Using radio waves or infrared sensors that detect physical attributes of waste such as weight, volume, or composition.

- **However, a CV model could be the best solution**

1) **Visual-based detection** Cameras can capture images which can identify and locate waste accurately. A CV model can analyze these images and detect trash with high accuracy.

2) **Flexibility** A CV model can be trained to detect different types of waste, which may not be possible with sensor-based solutions.

3) **Low-cost** The cost of deploying and maintaining a CV solution is relatively low.

4) **Real-time monitoring** real-time monitoring of waste allows for timely interventions.

5) **Scalability** It can be scaled for comprehensive coverage of the campus and accurate detection of waste across multiple locations.

Our Model Architecture

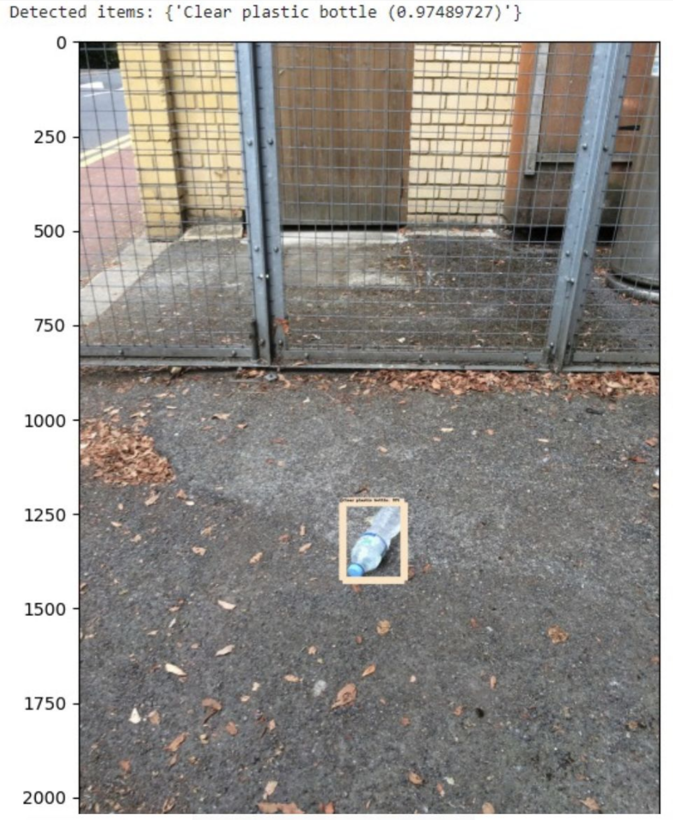
Mask R-CNN

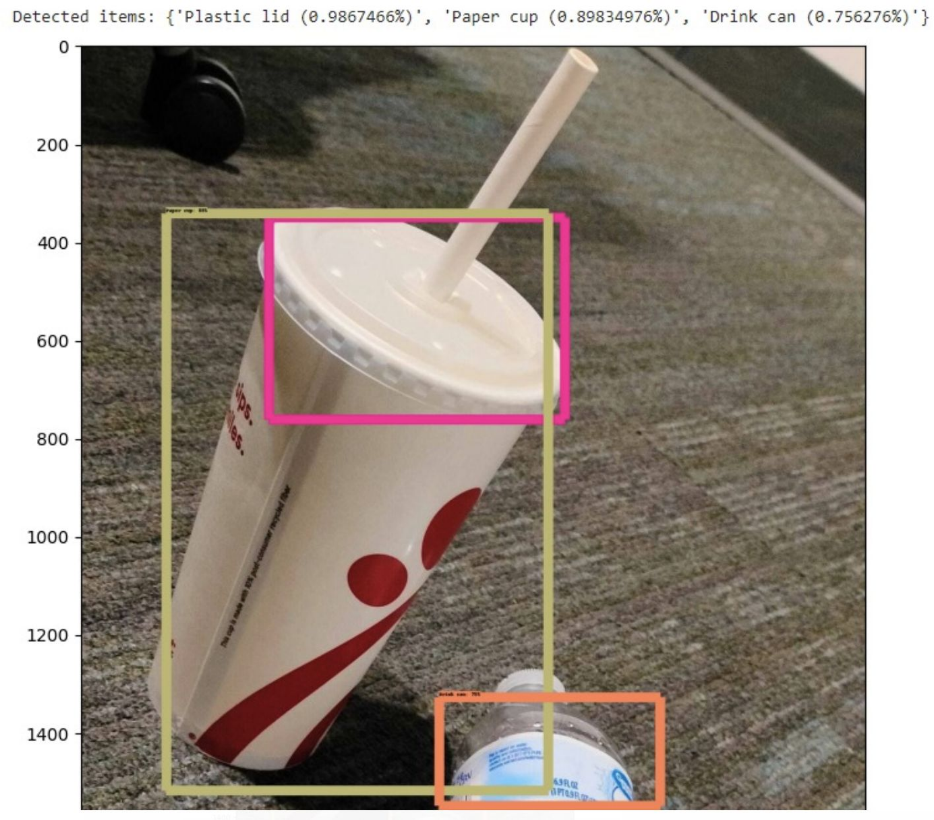
- is a popular object detection algorithm that builds upon the Faster R-CNN architecture by adding a segmentation mask branch,
- which allows for accurate pixel-level segmentation of objects.
- With the Mask r-cnn we are using a **backbone network spinenet 49** to extract features from the input image that can be used for object detection and instance segmentation.

Using backbone network

- Backbone networks like SpineNet 49 are used in Mask R-CNN to extract features from the input image that can be used for object detection and instance segmentation.
- SpineNet models are based on a "spinal" architecture that uses a backbone network to extract features from images, followed by a set of "spinal" modules that refine the features and generate final predictions.

Output


Detected items: {'Clear plastic bottle (0.97489727)'}
0
250
500
750
1000
1250
1500
1750
2000


Detected items: {'Plastic lid (0.9867466%)', 'Paper cup (0.89834976%)', 'Drink can (0.756276%)'}
0
200
400
600
800
1000
1200
1400

Outcome-Action Pairings

- True Positive (TP): Model correctly detects garbage in an image
- Action: Notification sent to maintenance staff and cleanup of specific location is necessary

- False Positive (FP): Model incorrectly detects garbage in an image where there is none
- Action: Maintenance staff will be falsely notified. Could implement a confidence level in the model detection, where only high confidence instances send a notification

- True Negative (TN): Model correctly identifies an image as non-garbage
- Action: None

- False Negative (FN): Model fails to detect garbage in an image where it exists
- Action: Garbage removal is still necessary although the staff was not notified

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CONCLUSION

Bias & Limitations

- Data bias: Training data may lack garbage diversity (type, location, etc.) that could result in biased results

- Label bias: Different interpretations of garbage (clean, dirty, etc.) are possible and can lead to poor performance

- Deployment bias: Factors such as lighting and image quality can differ from training data and impact output

- Limitations: Limited Data

Future Enhancements

- Utilizing Transfer Learning: This could help improve model accuracy in the future and we could benefit from pre-trained models
- Introduce environmental factors to training data: Adding images with noise such as rain to the training process could improve performance when these factors are present in new data
- Domain transfer: Improving performance in different environments (lighting, image quality) would be beneficial in terms of improving accuracies

References

- https://www.statepress.com/article/2021/03/spbiztech-asu-brings-new-waste-sorting-machine-to-campus
- https://www.kaggle.com/code/bouweceunen/garbage-detection-with-tensorflow

THANK YOU