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Optimization of Graffiti Detection in Autonomous Drones: Effect of Image Resolution and Confidence Threshold Tuning

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ABSTRACT

Not only does graffiti cleanup costs above $12 billion annually in the United States, it uses over 25,000 tons of carbon globally, requiring large trucks, cranes, and human labor to manually remove illegal graffiti. This shows the need for better and more efficient technology to reduce the cost. Although recently there is an introduction of using drones to clear graffiti, it depends on human control, requires a long time, and requires constant refilling of paint. This study designs an optimized graffiti detection machine learning model to be potentially used in graffiti removing drones and traffic cameras. We utilized transfer learning techniques by importing a pretrained YOLOv8 model to train on pre-processed dataset. To optimize the execution time and the average Intersection over Union (IoU) metrics of YOLOv8, we studied how image size and confidence threshold each affect the performance of the model. We found that the optimal image sidelength is 384 pixels and the average IoU increases with decreasing confidence threshold.

INTRODUCTION

Graffiti cleanup costs over $12 billion annually in the United States. Exploring technology that is more productive, cost effective, and safe would be beneficial for all over the country. Current technology not related specifically to graffiti cleaning drones would include Autonomous Un-manned Vehicles, that work on both detection and remediation. This technology is significant and puts graffiti drone technology into perspective since it would allow us to analyze the limits and benefits of this technology. One specific graffiti drone company that is successfully working in Washington would be the Aqualine Drones. This graffiti removal drone company works with drones and AI-powered cameras to take a proactive approach to combat graffiti. Some specific areas they target are graffiti on road, highways, and bridges nationwide, to improve infrastructure and help with community cleanup. Yet, this technology does have several limitations that we will address in our solution, some being object detection. As graffiti is a form of art and expression, it is crucial that we aren't entirely erasing it, and only implementing the technology in areas where graffiti is illegal. Precision spraying is also a limitation with current technology that we will be addressing, to minimize waste and environmental runoff.

The historical development of illegal graffiti removal proved gradual. In 1972 in New York, the Anti Graffiti Bill was passed after the explosion of Graffiti art (end of 1960s and start of 1970s). Intensified enforcement of Graffiti laws happened in New York during the 1980s. Anti-graffiti coatings started to appear in the 1990s. Graffiti removal was useful to conserving historical buildings or infrastructures. Workers shine high-intensity, pulsed beams to vaporize paint through sublimation, "detaching" it from surfaces. This laser technology was used as a removal technique for monuments like the West Kennet Avenue and Stonehenge in England between 1996-1998. From 2005 to 2008, the European Commission financed projects like GRAFFITAGE to prevent graffiti in walls. This project experimented with a pH neutral cleanser which is safe to be exposed to various substrates of the walls, which can consist of quartz-rich arkose.

Traditionally, graffiti removal was accomplished with the assistance of large trucks and cranes. While trucks and cranes burn a significant amount of fuel, drones can move quickly and produce minimal emission. Environmental sustainability is one of the reasons why recent innovations change focus on anti-graffiti drone designs.

On February 10 2024, the Substitute House Bill is an act passed regarding graffiti abatement and reduction programs. This is also the official bill which prompted many organizations to innovate anti-graffiti drones. The Substitute House Bill prompted drone pilot programs among which the leading program was organized by the Washington State Department of Transportation (Johnson, 2024). According to this bill, the department of transportation must complete a graffiti abatement and reduction pilot program. This program should include field testing spray drone technology to more efficiently paint over existing, illegal graffiti. Additionally, the department of transportation should develop a system to identify one's motion of painting graffiti.

In this study, the YOLOv8 models will output the predicted coordinates of the upper left and bottom-right corner of the bounding boxes (x1,y1) and (x2, y2). The same approach is used by other research papers, because it provides the difference between the predicted box and the ground truth. (Zhao et al., 2019)

MATERIALS AND METHODS

For the purpose of our research, this study uses the dataset "Graff Computer Vision Model" found from https://universe.roboflow.com/graff/graff-ymab0/dataset/2/download/yolov8. The dataset has three subsets: training, validating, and testing. Each subset includes one annotation.csv which tabularizes image filenames and labels. The rest of the files in the subsets are the image files listed in annotations. There are one or multiple boxes of graffitis in each image. Pre-determined by the dataset, 1397 of all data is used for training, 350 for validating and 32 for testing.

a) The dataset contains images with multiple graffiti. An example is in Figure 1.

Figure 1: an example of an image from the raw data, containing graffiti with dimension 640 by 640.

b) The width and height of all images in the dataset are set to 640 by 640.
c) Class: Graffiti. All images in the dataset consist of graffiti in some region of the image.
d) The output is an array of integers in the format [xmin, ymin, xmax, ymax]. They are the coordinates of the upper left and bottom right corner where the graffiti lies in the image.

YOLOv8 requires a specific folder structure. The dataset should include two directories, images/ and labels/, and a data.yaml file. Within each directory, there are sub-directories such as train/ and val/. Because the original, publicly accessible dataset does not follow such format, conversion code is needed to change the names of directories and to rename the filepath.

Next, a data.yaml file is created. A data.yaml file is a human readable data serialization format and processing model. It describes a class of YAML Documents, as well as how the computer program processes them.

Train-Test Split

Machine learning models will train from a dataframe, learning various inputs and outputs, so that it predicts the correct output when encountering new data. However, if the model could access all of df, the model could memorize the training data instead of learning from it and we would not be able to identify that as we would not have additional data to test the model. We need a train-test split in order to evaluate the models when they encounter datasets they have not seen. In our approach, 1397 of all data is used for training, 350 for validating and 32 for testing. These numbers are predetermined from the Kaggle dataset.

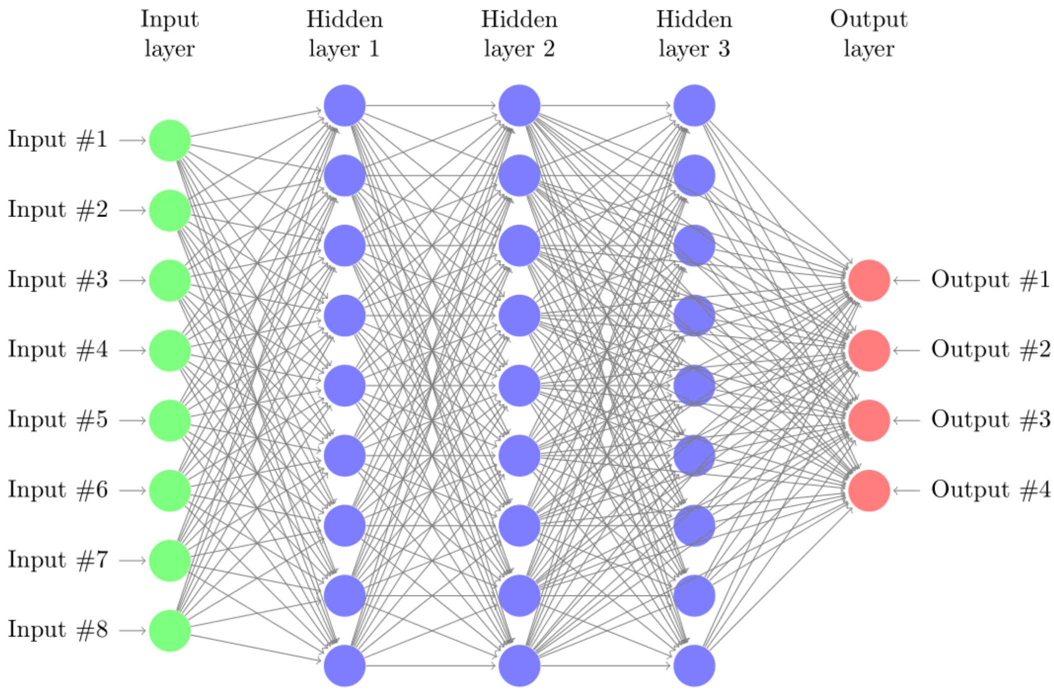


Figure 2: A demonstration of a multi-layer perceptron neural network algorithm with inputs and multiple hidden layers that generates an output out of four predictions (MLP-Illustration 2024).

Transfer learning

The YOLOv8 model is a type of Convolutional Neural Network.

We used transfer learning by importing YOLO from Ultralytics. After loading the pre-trained model, we trained YOLOv8 on the pre-processed Kaggle dataset.

In this study, we use the intersection over union(IOU) metric to evaluate different YOLOv8 models. The average IOU value of all predictions is calculated, and the maximum IOU value of a prediction ever generated by each model is found. We choose the IOU metric because we penalize the predictions which cover the entire image, as well as the predictions which do not position the graffiti at all.

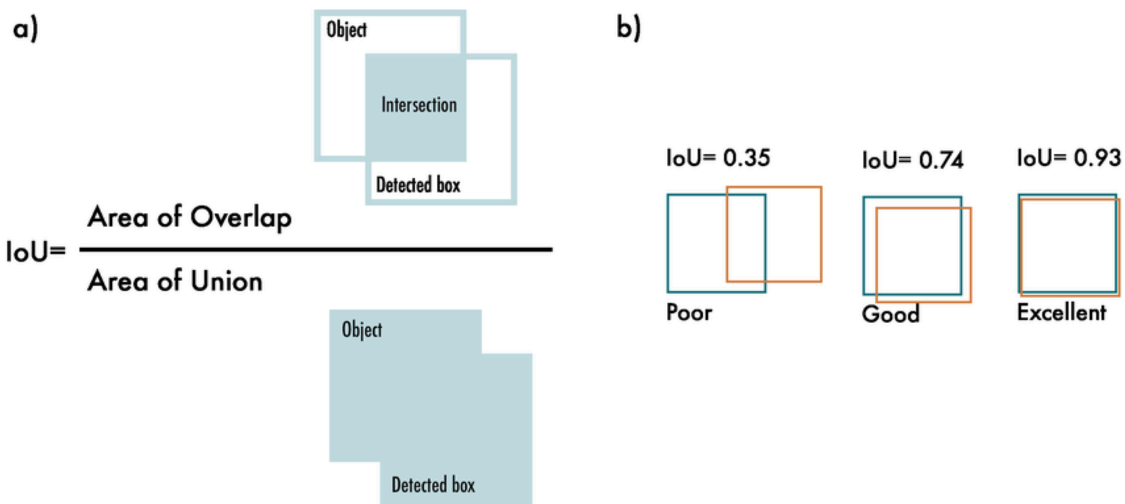


Figure 3: a) The IoU (intersection over union) metric is calculated by dividing area of overlap between the detection and ground truth, with the union of both rectangles. b) The IoU metric reflects the quality of object detection.

We changed two hyperparameters - image sidelength and confidence threshold - and compared the change in the model's performance, such that we can decide a model with optimal execution time, average IoU, and fraction with IoU >= 0.5.

Models 1-4 have image sidelength 640, 512, 384, and 320, respectively. We then decided among these four that it has the lowest image sidelength and the smallest reduction in average IoU and fraction with IoU >= 0.5. This is because the smaller the image size, the shorter execution time it takes. We want a model with the least running time, while maintaining similar performance as those of higher running times. After we find such a model, we maintain its image size but replicate it into models 5-8 and alter the confidence threshold when the model is predicting. Lowering the confidence threshold increases the mean IoU and the fraction with IoU >= 0.5.

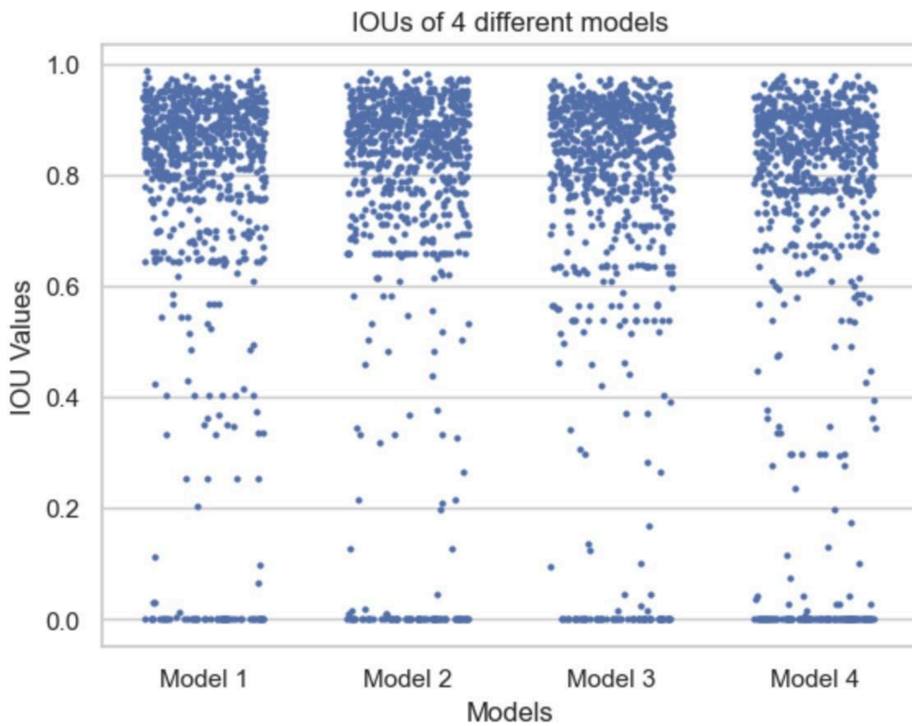
RESULTS

Epoch = 1, Image size = 640, batch=16,
Using the YOLOv8-n model, a YOLOv8 model which has the fastest running speed but lower accuracy, the mean IoU is 0.1626.
Moreover, 18.63% of all predictions overlap with the ground truth by at least 50%.

Table 1: With constant epoch = 10, various YOLOv8-n models with different hyperparameters (image size) predicted results with various IoU.

Model	Image Size	Time executed	Mean IOUS	Max IOUS	Index of max IOUS	Fraction with IOU >= 0.5
1	640	306.047600	0.775475	0.986083	721	0.896071
2	512	241.145020	0.760656	0.985345	31	0.885932
3	384	191.968374	0.760772	0.980032	569	0.896071
4	320	169.441592	0.713078	0.979054	132	0.831432

Graph 1: With constant epoch = 10, the IOU value spans from 0 to 1 in four different models. As the image dimension decreases, the IOU spread shifts downward slightly and the number predictions with IOU near 0 increases.



Graph 2: With constant epoch = 1, the IOU value spans from 0 to 1 in four different models. As the image dimension decreases, the IOU spread visibly shifts downward and the number predictions with IOU near 0 increases.

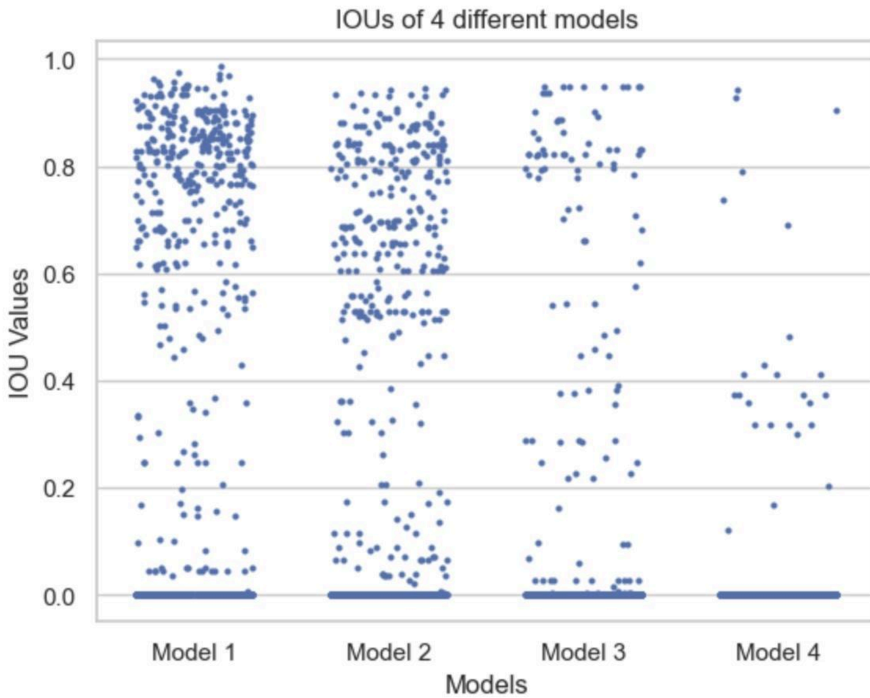


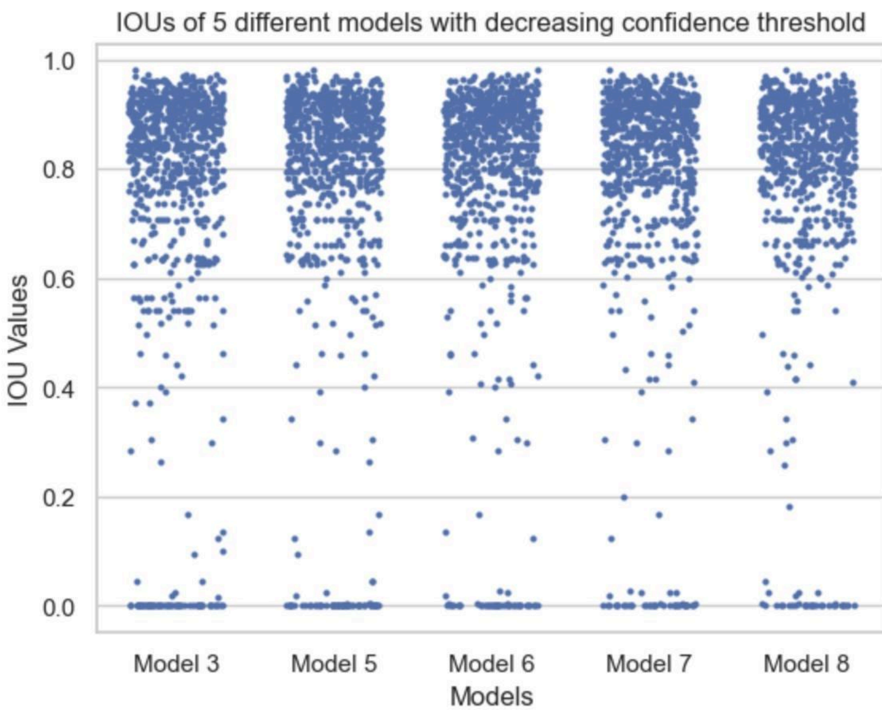
Table 2: With constant epoch = 1, various YOLOv8-n models with different hyperparameters (image size) predicted results with various IoU.

Model	Image Size	Time executed	Mean IOUS	Max IOUS	Index of max IOUS	Fraction with IOU >= 0.5
1	640	66.615608	0.326293	0.985452	84	0.390368
2	512	55.025819	0.232796	0.944737	676	0.296578
3	384	50.311348	0.074251	0.948641	470	0.077313
4	320	42.963031	0.014476	0.944044	507	0.007605

Table 3: With constant epoch = 10 and image size = 384, five YOLOv8-n models with various confidence thresholds predicted results with various IoU.

Model	Confidence Threshold	Time executed	Mean IOUS	Max IOUS	Index of max IOUS	Fraction with IOU >= 0.5
3	0.25	202.984627	0.760772	0.980032	569	0.896071
5	0.20	14.731374	0.769393	0.980032	569	0.903676
6	0.15	6.787518	0.784373	0.980032	569	0.918885
7	0.10	7.972862	0.791358	0.980032	569	0.929024
8	0.05	7.265816	0.801137	0.980032	569	0.937896

Graph 3: With constant epoch = 10, the IOU value spans from 0 to 1 in four different models. As the image dimension decreases, the IOU spread shifts downward slightly and the number predictions with IOU near 0 increases.



DISCUSSION

Future research can focus on implementing Anti-Graffiti AI technology in drones, enhancing their cameras and sensors. These types of drones could be automated to navigate itself along the sides of highways to detect illegal graffiti. In ten or more years, anti graffiti technology can be autonomous, using drones to detect places with graffiti and clear areas with precise spraying tools without constant human control. Future technology uses Artificial Intelligence to detect and remove graffiti in a short amount of time compared to current methods which can take up to 2-4 hours for medium sized graffiti drawing areas (FCT Surface Cleaning, 2025). This autonomous drone network can help reduce cost, speed graffiti removal and remove risks which are present in the current solution, tethered drones. Our Autonomous Anti-Graffiti Drone Network would run with the help of images from traffic cameras, satellite imagery, and an AI system to detect places with graffiti accurately. One person is able to overlook multiple drones, which are dispersed at various locations along places where graffiti is common. The central system that the person uses consists of GPS, tracking the location of each drone. The GPS system also guides each automated drone to navigate along a certain highway. Such an advanced feature prevents the drones from going off-bounds or deviating from their objectives.

The AI system will use edges, color, texture, strokes, shapes, and text, comparing one region with its surroundings, to find the regions that are vandalized. Then, the drone sensor will run through databases to verify that the area should not have graffiti (e.g. highways, bridges) and it is safe to clean without violating any policies. After detecting illegal graffiti, the drone sends a signal to the map of the central system. Meanwhile, traffic cameras could also send illegal graffiti locations to the system. These improved traffic cameras along highways and roads feature motion capture. Not only will they locate the newly painted illegal graffiti, they will also find the people responsible for vandalism, becoming the essential evidence in court for charging one for vandalism. By using upgraded traffic and surveillance cameras with motion detection and proper time stamps with GPS location, the system can capture video of people when they are vandalizing and it will send this to law enforcement agencies to investigate.

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