YOLO Modeling to Detect Uranium

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Introduction

The YOLO model, renowned for its real-time object detection capabilities, has been adapted and fine-tuned to address the challenges posed by the detection of uranium, a material crucial to both peaceful and potential nefarious applications. The proposed model leverages convolutional neural networks (CNNs) to efficiently process high-dimensional data, allowing for swift and precise identification of uranium signatures within various imaging modalities. The methodology involves the collection of diverse datasets encompassing different scenarios, including varying lighting conditions, backgrounds, and shieldings. The YOLO model is trained on these datasets, employing transfer learning to enhance its adaptability to specific uranium detection tasks. The results demonstrate the model's effectiveness in accurately localizing uranium sources while minimizing false positives. Furthermore, the study evaluates the model's robustness against potential adversarial attacks and its generalization across different sensor platforms. The implications of deploying YOLO-based uranium detection systems in real-world nuclear security applications are discussed, emphasizing the importance of real-time monitoring and rapid response to potential threats.

Objective

The importance of utilizing YOLO modeling for the detection of uranium in nuclear security applications lies in the critical need for swift and accurate identification of radioactive materials to prevent potential threats and ensure public safety. This speed is crucial for timely responses to potential threats, allowing security personnel to take appropriate actions swiftly. This is essential to minimize false positives and negatives, ensuring that security systems provide reliable information for decision-making. This adaptability enhances the model's performance in real-world applications where conditions may vary. This enhances our ability to respond effectively to potential threats and protect public safety.

Materials and Methods

Ultralytics

Images of uranium

Results

For our dataset, we utilized Roboflow, a platform that provides tools for creating datasets, training models, and deploying to production. Roboflow allowed us to bring in images in various annotation and image formats via API. We were able to filter, tag, segment, preprocess, and augment image data by metadata, train/test split, or location of image. This helped us to create a robust and diverse dataset for training our model.

In all three graphs, an epoch is one complete pass through the entire training dataset. The model's accuracy is a measure of how well the model performs on the validation set. The different colors in each graph represent different metrics used to measure the model's performance. The goal is to have the highest possible accuracy, which would mean the model is doing a good job predicting the validation data.

Our Results

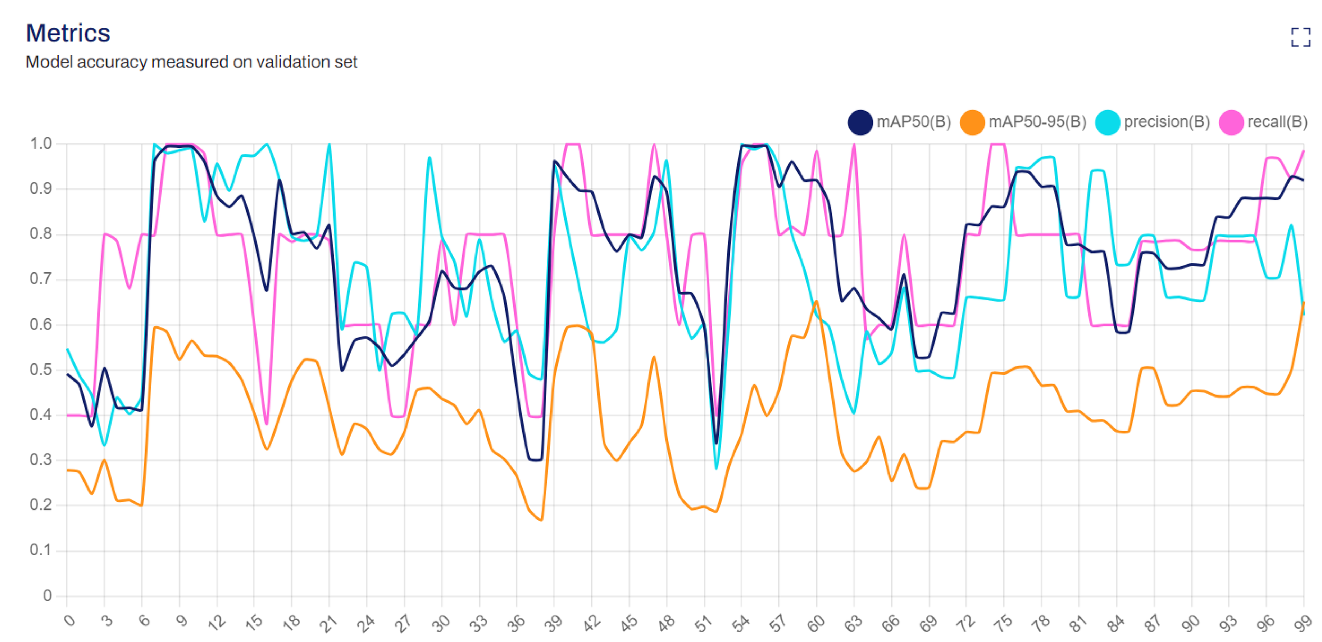


Figure 1: Model accuracy measured on validation 3rd set

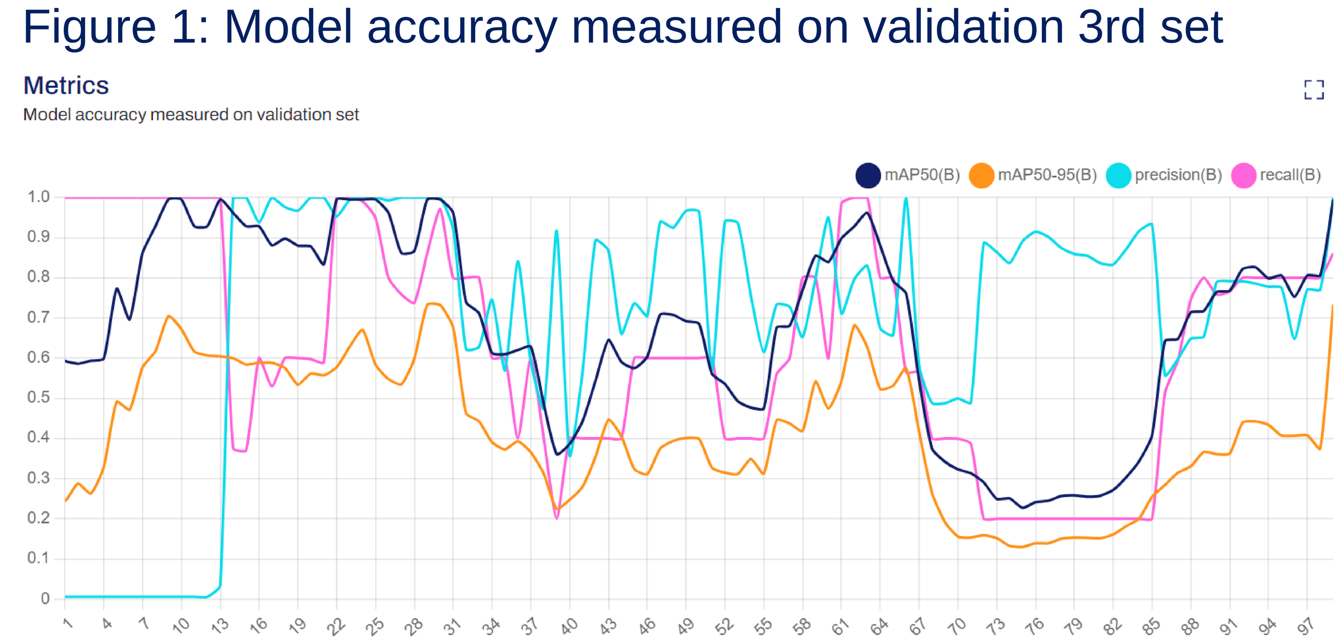


Figure 2: Model accuracy measured on validation 2nd set

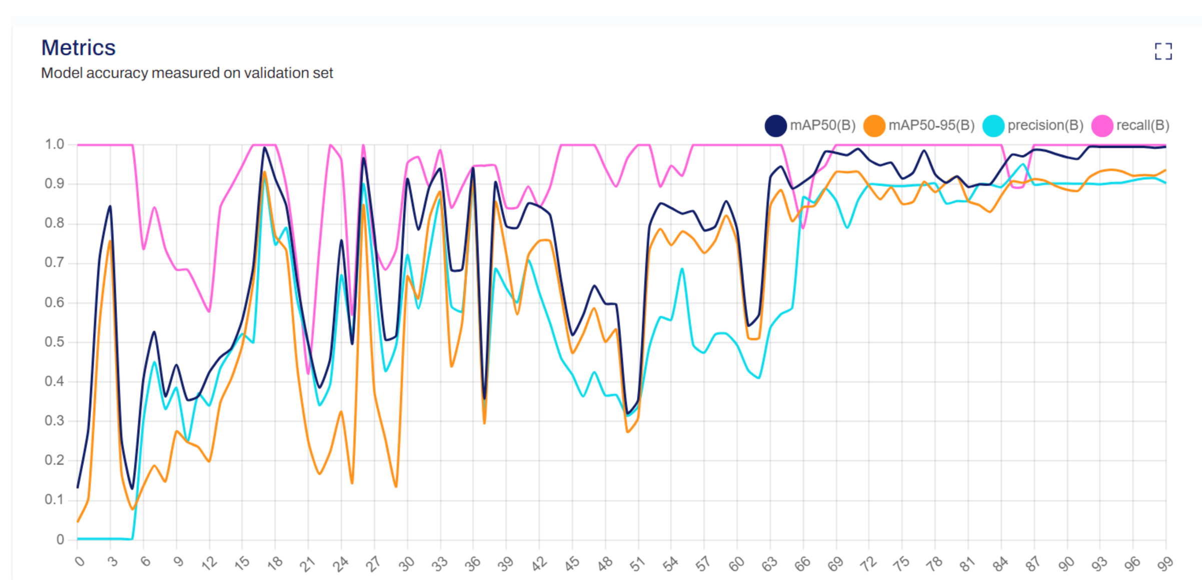
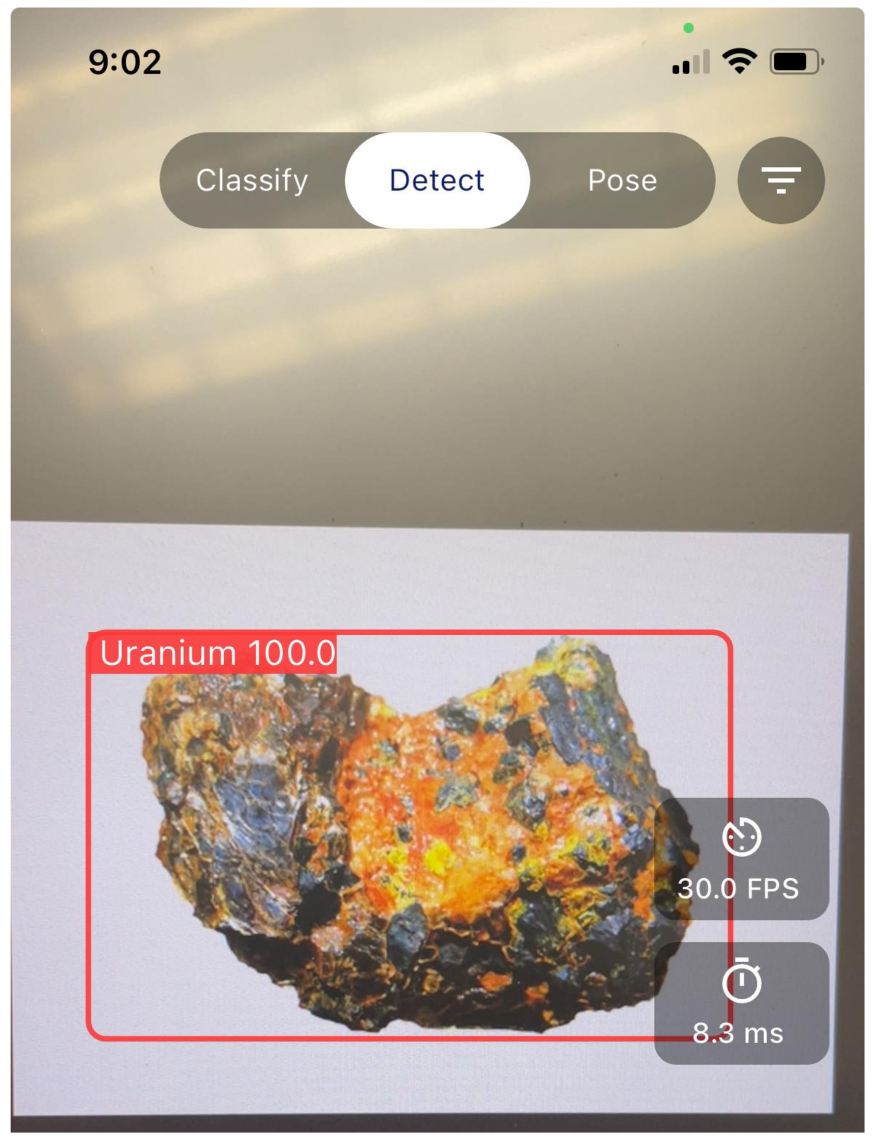


Figure 3: Model accuracy measured on validation 1st set



Summary and Conclusions

YOLO has been renowned for its real-time object detection capabilities and has been adapted to address the challenges posed by the detection of uranium. Through trial and error, the latest version of this program has been pushed to its limits in the hopes of detecting uranium by using Ultralytics implementation. As it is shown in Figures 4 through 12, it can be said that the program is gradually learning on how to detect Uranium with each trial being more accurate than before. With the project ending after Figure 12, one could say that, should the trials resume and continue, the program will become more accurate in determining uranium. The overall objective of this project was to train an object detection system, such as YOLO, into locating, determining, and classifying an object as either Uranium or not. From the data that was taken, it can be concluded that the goal was achieved and the methods that were applied to this project can be applied to other YOLO projects in the future.

References

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