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WBS # – Project Title: 24.1.3.2 – Deep Learning Algorithm

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Summary Statement of Work: In this project, Brookhaven National Laboratory (BNL) and Sandia National Laboratories (SNL) are jointly developing deep machine learning algorithms to improve the review process of surveillance data by identifying objects of interest in image-review software. The technique being developed in this project can be used to reduce the burden on International Atomic energy Agency (IAEA) safeguards inspectors during surveillance review.

Major Highlights: In this year, the team adaped the You Only Look Once (YOLO) deep machine learning algorithm to surveillance data review for nuclear safeguards-relevant applications. Initial results from YOLO at test facilities at BNL and SNL have demonstrated high precision in identifying objects of interest. The following list of tasks has been carried out successfully this year.

- The team worked with NA-241 and the IAEA to develop use cases of the technology and a research plan for object detection task for FY18.
- The team located test facilities at both BNL and SNL.
- The team acquired and/or borrowed surveillance cameras from AQUILA and the IAEA, and installed the cameras at the test facilities.
- The team collected videos from the surveillance cameras and still images from commercial digital cameras and smart phones at the test facilities for algorithm training and testing.
- Both BNL and SNL trained and tested the YOLOv3 model independently, including a cross-site data collection and model validation activity.
- BNL conducted validation test and developed an incremental transfer learning method for deployment of the YOLOv3 model in fields.
- SNL conducted validation tests for determining the viability of using a single model between multiple sites.
- The team submitted a full paper for presentation at the IAEA Symposium on International Safeguards in November 2018.

Accomplishments by Tasks:

<u>Task 1 – Develop use cases and work plan</u>

In order to develop meaningful goals and a productive work plan, we held three meetings with NA-241 and the IAEA Department of Safeguards Division of Scientific and Technical Services (SGTS) Surveillance Team. The main purpose was to consult with the IAEA regarding the potential use cases of our technologies, the IAEA's priorities in addressing the challenges related to surveillance review and the IAEA's requirements in advanced software features to enhance the review process.

The first meeting was a virtual meeting at the beginning of FY2018. At this meeting the IAEA explained the status of camera replacement and review systems. The team learned that the Next Generation Surveillance System (NGSS) was replacing the standard digital camera module (DCM-14) cameras worldwide. The legacy General Advanced Review Station Software (GARS) system was not being replaced and has limited functions to use the new features of NGSS or integrate inputs from other types of sensors. The IAEA also explained the operation of safeguards surveillance systems and the image storage and review process. We learned that the technologies we proposed could be beneficial to international nuclear safeguards.

The second meeting was a face-to-face meeting in Vienna in December 2017. Yonggang Cui from BNL and Maikael Thomas from SNL attended the meeting on behalf of the research team. We presented our ideas in detail and demonstrated the results of our feasibility studies at test facilities at both Labs. We answered the questions and addressed concerns that the IAEA SGTS Surveillance Team had regarding applications of deep learning algorithms in image review and potential usability issues in field deployment.

The third meeting was a phone meeting on January 21, 2018. In the meeting, we received the IAEA's feedback on the ideas that BNL and SNL presented at the previous meetings. The IAEA stressed that the Deep Learning project was of high interest to many in the Safeguards Department. To support this project, the IAEA gave the team access to GARS image review software and loaned two NGSS cameras for data collection.

In addition, we were able to discuss the project with Ania Kimberley Kaminski, a contractor to Oak Ridge National Laboratory and an alumnus IAEA inspector. Ania described her experience as an inspector reviewing safeguards surveillance data. We learned that safeguards surveillance data is regularly collected atpressurized heavy water reactors (PHWR), pressurized water reactors (PWR) and boiling water reactors (BWR). Reviewing the surveillance videos of these facilities is time-consuming with current image review tools, and the technology being developed in this project is of high interest in these applications.

Based on the results of these meetings, we generated a list of use cases (Table. 1) that we may be able to address with deep machine learning techniques.

After consultation with the IAEA, we held a technical kick-off meeting at BNL on February 13^{th,} 2018, to examine all the use cases in terms of resources, suitable algorithms and risks. Based on the input of the IAEA, we created the following work plan for this project:

- Year 1: Develop YOLO convolutional neural network (CNN) for object detection capabilities, focusing on detecting and monitoring cask movement in reactor halls
- Year 2: Develop Re-ID technique to track cask movement from reactor hall to loading bay, truck, and then dry storage, and evaluate the Pred-Net generative approach for detecting anomalous activities within surveillance data
- Year 3: Develop algorithms image review of underwater cameras

Table 1. List of use cases

1. Object detection and tracking
  1) PWR/BWR - Cask loading process
    a. Detect and monitor cask movement within reactor hall
    b. Detect and monitor bridge movements
  2) PWR/BWR - Reactor outage process
    a. Detect and monitor objects moving in and out of hatch
    b. Detect and monitor bridge movements
    c. Detect and monitor fuel assemblies under water
    d. Detect and monitor movement of MOX under water
  3) PHWR
    a. Detect and monitor cask movement in reactor hall
    b. Detect and monitor cask under water
    c. Detect and monitor underwater fueling machine
    d. Track cask movement from reactor hall to loading bay, truck, and then dry storage.
  4) Enrichment Monitoring
  5) Reactor/Spent Fuel Pool Rippling Effects
  6) Bulk Handling/Reprocessing Monitoring
2. Activity pattern learning and anomaly detection

<u>Task 2 – Collect data sets</u>

1. Camera installation

Given the unavailability of nuclear facility images, the team set up test facilities at both labs to collect surveilience data. BNL used the Waste Management facility as a mockup of nuclear facility for material transfer, packaging and storage. SNL used its Gamma Irradiation Facility (GIF) due to its floor vault resembling a spent fuel cooling pond, and the Technology Training and Demonstration Area (TTD) for data collection. Camera deployments are shown in Fig. 1.

The team used three types of cameras for data collection.

1. NGSS cameras. NGSS cameras are the primary cameras for data collection in this project. The cameras were configured to take images at an interval of one second.
2. IP cameras. DINION IP ultra 8000 MP cameras were used in this project for two purposes. One was to compensate the data collection by the NGSS cameras by increasing the variety of the data set (different view angles and heights). The other

camera was future-looking to collect additional data of the experiments in different field of view so the data set can be used later for object tracking tasks.
3. Phone cameras. The team also used smart phone cameras and digital cameras to take still images to mimic inspectors taking images in nuclear facilities.

To ensure the same configuration of the YOLOv3 network, both BNL and SNL models had three classes of objects in the object detection task. At BNL, the classes of the object were 55-gallon drums, white container and yellow container as shown in Fig. 2. At SNL, the classes of the object were SNL container and gantry crane (Fig. 3) and a facility crane (not shown).

(b)

(a) (c)

Fig. 1 Installation of NGSS cameras. (a) BNL Waste Management facility; (b) SNL Technology Test and Demonstration Area; and (c) SNL GIF facility.

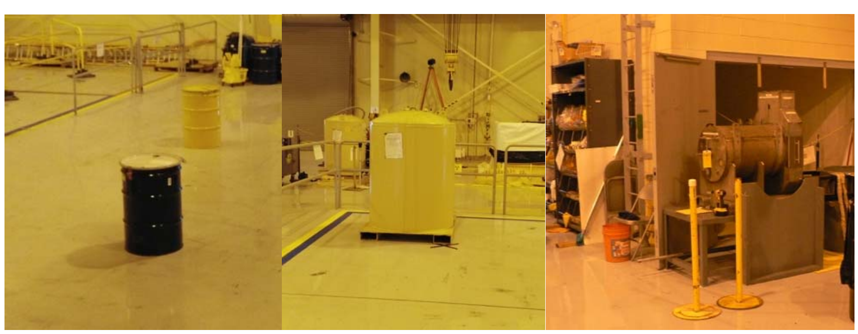


Fig. 2 BNL object classes. From left to right: 55-gal drum (black and yellow), large yellow container, and pig container.

Fig. 3 SNL object classes: white cylindrical containers, being hoisted by the blue gantry crane.

2. Data collection

For data collection, the team conducted dedicated experiments at the test facilities, e.g. positioning objects at specific locations and moving objects across fields of view of the cameras. Besides these controlled experiments, the team also collected images of real operational activities at the Waste Management facility at BNL and Gamma Irradiation Facility at SNL. Such uncontrolled scenes help make the data sets closer to the actual operational scenarios at nuclear facilities.

3. Video/image annotation

The team used available software tools, Vitbat for video annotation and LabelImg for image annotation. Given the variety of data sources (NGSS cameras, Bosch IP cameras and phone cameras) and data types (.mpg videos and .jpeg images), the team developed a workflow for annotation in which we consolidate annotation information of data to VOC XML format and videos/images to annotated .jpg files. These centralized formats allow the transformation of information to other formats required by a specific algorithm, e.g., YOLO XML for YOLO CNN (Fig. 4).

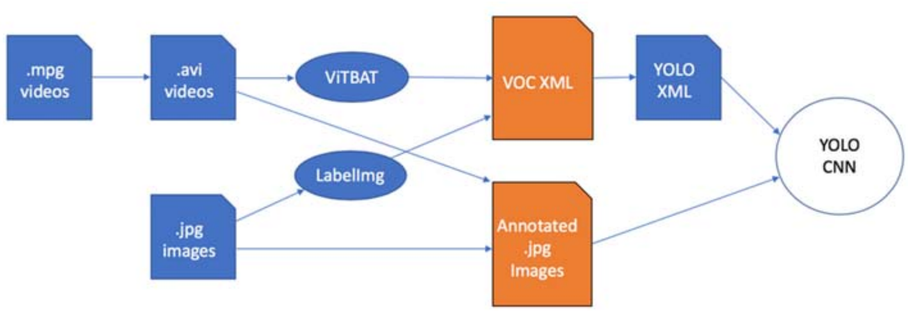


Fig. 4 Workflow of data collection and annotation

Task 3 – Development of the deep learning algorithm

1. Training the YOLO v3 model

The source code of the YOLO v3 model is open-sourced. The initial weights, pre-trained on the large image dataset (ImageNet), are used to provide a good starting point and to reduce amount of additional training. We used the default hyperparameters of the model have been optimized for training on public benchmark datasets such as PASCAL-VOC and MS-COCO.

BNL experimented with several different hyperparameter settings and found the following settings work well. The default learning rate of 0.001, momentum of 0.9 and decay rate of 0.005 were used. The batch size was optimized to 24 in order to fully utilize the GPU computation device. We recompute the anchor boxes using the K-means clustering algorithm on the bounding boxes of our data. We identified that at about 8000 iterations (about $2\text{x}10^5$ images are seen), the model performs well without overfitting. Fig. 5 shows two examples of the detection results in which most of the objects of interest were detected with good accuracy. Fig. 6 shows the quantitative results of the latest training process. We were able to reach a high mean Average Precision (mAP) value across the three classes of objects of 85.3%, which is higher than the value of 80.66% we reported in the full paper submitted to the IAEA Safeguards Symposium in mid-August.

Fig. 5 Example images of object detection by the YOLO v3 model. The images show the operation of the BNL Waste Management facility. Three defined classes of objects were detected with good accuracy.

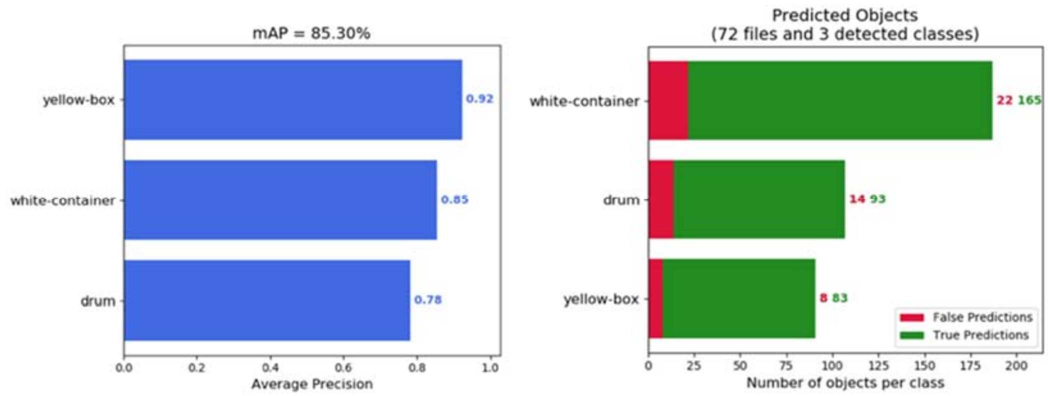


Fig. 6 Quantitative results of the YOLO v3 model trained at BNL

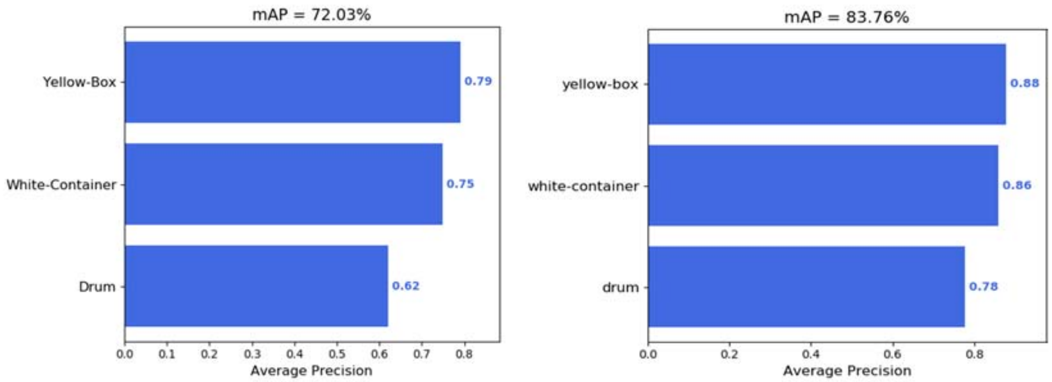
SNL trained several models based on different assumptions regarding access to safeguard surveillance images. Similar to BNL, SNL trained a model using NGSS data from our test facility. The average precision for detecting the SNL white container was 90.91%. The average precision for detecting the two cranes was 100%.

SNL also tested a model with the assumption that NGSS data would not be available to train and validate the model. Under that assumption, we collected 264 images of the SNL container collected on smart phone cameras, all of which were taken outside of the test facility (including in storage, in an office setting, and from testing facilities outside of SNL). In addition, we collected 50 images of gantry cranes and 90 images of facility cranes from open sources. When used on the iphone dataset, the model trained had an average precision of 81.05% for the SNL container, 90.91% for the overhead crane, and 90.91% for the gantry crane. When we testedthe model on the NGSS data recorded within the GIF test facility, our model experienced an anticipated drop in performance due to the unfamiliar environment, with an average precision of 18.05% for the SNL container, 0.37% for the gantry crane (which was only partially visible in our NGSS dataset) and 0.0% for the overhead crane.

2. YOLOv2 vs YOLOv3

At the beginning of the project, the team reported the results of a feasibility study with YOLOv2. Shortly after that, a new version, YOLOv3 was released. The BNL team conducted a quick test to compare the two versions with a small image set and noticed that YOLOv3 had significant performance improvements in terms of detection accuracy and execution speed. Given this observation, the team decided to move the development work from YOLOv2 to YOLOv3.

Fig. 7 shows the comparisons between YOLOv2 and YOLOv3 on three object classes in the BNL data set. Fig. 7a is the result of the feasibility study with YOLOv2 at the beginning of the year. Fig. 2b is the performance of the YOLOv3 on the same data set at the end of the year. The main average precision increased significantly from 72% to 84%.



(a) (b)

Fig. 7 Comparisons of average precision and main average precision between YOLOv2 (a) and YOLOv3 (b) on the BNL data set.

3. Cross validation

A validation test was conducted at the end of the year to demonstrate the practical way to deploy the transfer learning technique and the YOLOv3 model in the field.

In this test, the YOLOv3 model was trained first on an external domain data set collected in environments not related to a validation facility where the YOLOv3 model would be deployed for video reviews. Once the training was done, it was applied directly to the validation data set. Given the model hadn't learned any background information of the facility, the detection performance was poor as expected. Then, the model was re-trained following an incremental process in which a number of images from the validation facility were added to the domain data set gradually. At each training step, the model was tested with the validation data set.

Fig. 8 shows the result of the incremental training test. The dashed line "1" indicates the case in which the model was trained completely with an internal data set that was collected at the validation facility. The data set contained about 425 images. Since the training and testing data sets were both from the same facility, the model gave the best or optimal performance with a high mAP value of 83%. We called this case the direct transfer learning. The circled point "2" indicates the case when a model was trained with external domain data set, as mentioned above, and then applied directly to the facility data set. Since the model didn't have full knowledge of the facility, especially the background settings, it performed poorly with a low mAP value of about 30%. In the subsequent incremental learning process, small image sets of 10, 25, 50, 100, 140 and 173 images were added to the domain training data set. These additional images helped train the YOLOv3 model better as they added more facility specific information to the model. For example, with 25 additional images, the mAP value of the model could be doubled. With 100-150 additional images from the facility, the detection performance of the model is getting close to the optimal performance of the direct transfer learning as represented by the dashed line. In figure 7, the results of the added images are indicated by "x".

This validation test demonstrated that incremental learning is a practical approach fordeploying the YOLOv3 model and transfer learning technique in the field. The advantage of the incremental learning is less effort required in field to prepare the training data set. Comparing to the direct transfer learning, this effort can be reduced more than 50% in the incremental learning. This could be especially significant in facilities where images are not permitted to leave the site, requiring that any deep learning model be trained (and permanently stored) on-site.

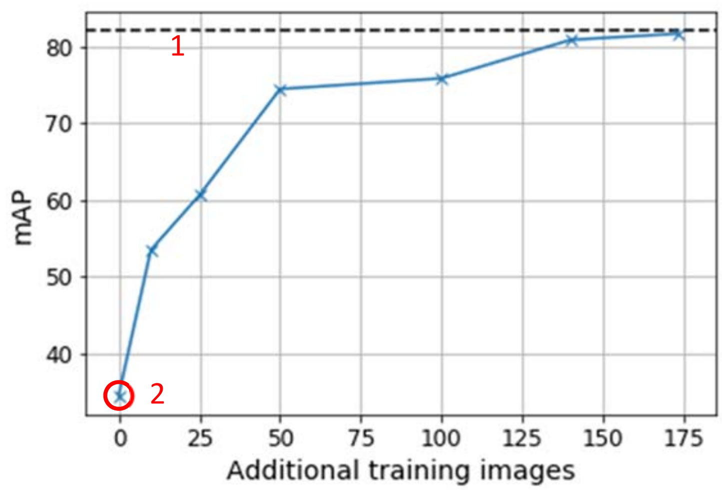


Fig. 8 Performance enhancement of the YOLOv3 model through the incremental learning technique.

4. Developing in-depth understanding of YOLO v3 model

The resulting predictions from the model are sorted according to the "objectness" score with a cutoff threshold θ. A well-trained model will yield a bimodal distribution of the regions' objectness at 0 (not containing an object) and 1 (containing an object). Therefore, picking θ around 0.5 balances the precision and recall. BNL qualitatively experimented to determine how θ would affect recall and precision values. For example, in circumstances where users may prefer high recall (i.e. limiting the number of potential false negatives), θ may be set to a very low value such as 0.01 to increase recall with the cost of lower precision. However, we also found that the variation of this trend depends on the object in question and realized that it could be valuable to conduct more experiments with actual IAEA objects and data sets.

5. Developing an autonomous program for training model

Training the model is a repeated task in the model development process and the future model evaluations and implementation on the users' end. Currently this is done manually with the developer's interference to check the accuracy and convergence of the model. BNL realized that a program to automate this process would save time in algorithm development. We initiated this work and wrote some scripts for test purposes. We plan to continue this task because it can also be used by end users to lower the burden in the training task and facilitate the algorithm training process, thus easing preparation for field deployment of the model.

Summary A YOLOv3 model was adapted for object detection in surveillance image review. The promising test results on images from the test facilities showed state-of-the-art object detection performance. The validation test results demonstrated that by using incremental learning, the YOLOv3 model is a useful tool in fields that would potentially increase the efficiency of the tedious image review process.

Presentations:

1. Yonggang Cui, “Using deep learning algorithms to enhance image-review software for surveillance cameras”, presentation to the IAEA Surveillance Support Team, Vienna, December 6, 2017.
2. Maikael Thomas, “Object recognition and anomaly detection in IAEA video surveillance”, presentation to the IAEA Surveillance Support Team, Vienna, December 6, 2017.

Publication:

Yonggang Cui, Zoe Gastelum, Yihui Ren, Shinjae Yoo, Yuewei Lin, Michael Reed Smith, Maikael A Thomas, Warren Stern, “Using deep machine learning to conduct object-based identification and motion detection on safeguards video surveillance”, in Proceedings of the 2018 IAEA Symposium on International Safeguards: Building Future Safeguards Capabilities, November, 2018.